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Mapping Vegetation Complexes with Digitized Color Infrared Film Wisconsin Power Plant Impact Study

Wisconsin Univ.-Madison

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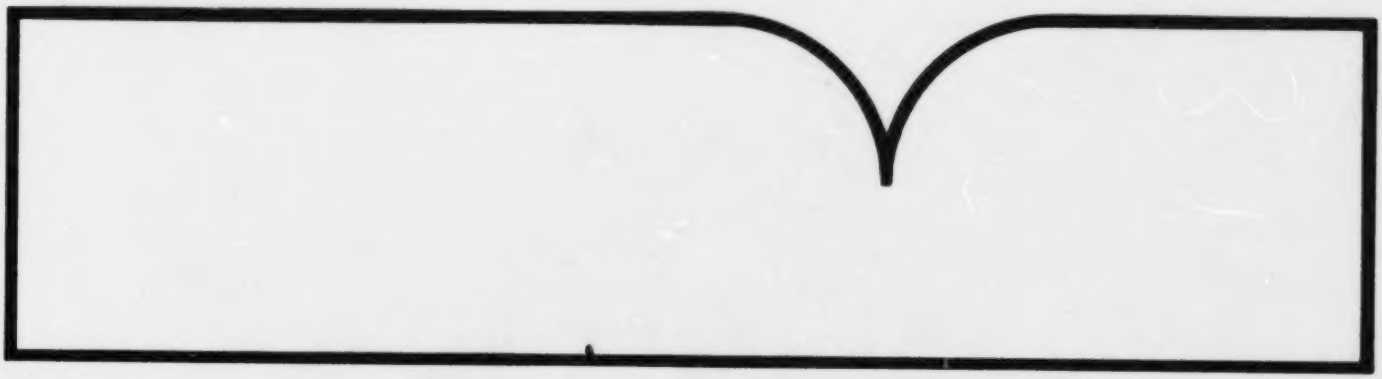

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Mapping Vegetation Complexes with Digitized Color Infrared Film

Wisconsin Power Plant Impact Study

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Some images were successfully classified, but other classification attempts were abandoned; digitized film analysis was not an entirely reliable mapping technique. Resource signatures often overlapped. Additional research should determine if multiseasonal data overlayment, data-enhancement transformations, and machine adjustments can create the necessary reliability for operational applications.

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MAPPING VEGETATION COMPLEXES WITH DIGITIZED COLOR INFRARED FILM

Wisconsin Power Plant Impact Study

by

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and Wisconsin Department of Natural Resources

ENVIRONMENTAL RESEARCH LABORATORY-DULUTH
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FOREWORD

The U.S. Environmental Protection Agency was established as a focus of scientific, governmental, and public efforts to improve the quality of the environment. These efforts require expansion of our understanding of the mechanisms that govern environmental changes and in particular those changes that result from our own manipulations of the environment. One specific thrust of these efforts must be the continuous development of more effective and more efficient methods for analyzing the environment and the changes occurring in it.

One such project, which the Environmental Protection Agency is supporting through its Environmental Research Laboratory in Duluth, Minnesota, is the study "The Impacts of Coal-Fired Power Plants on the Environment." The Columbia Generating Station, a coal-fired power plant near Portage, Wis., has been the focus of all field observations. This interdisciplinary study, involving investigators and experiments from many academic departments at the University of Wisconsin, is being carried out by the Environmental Monitoring and Data Acquisition Group of the Institute for Environmental Studies at the University of Wisconsin-Madison. Several utilities and state agencies are cooperating in the study: Wisconsin Power and Light Company, Madison Gas and Electric Company, Wisconsin Public Service Corporation, Wisconsin Public Service Commission, and Wisconsin Department of Natural Resources.

Reports from this study will be published within the EPA Ecological Research Series. They will deal with topics related to chemical constituents, chemical transport mechanisms, biological effects, social and economic effects, and integration and synthesis.

The Remote Sensing Group of the Columbia Generating Station impact study has sought to develop new techniques involving aerial photography of land areas--techniques that can be used to measure the impact of such facilities as power plants on the surrounding vegetation. This report describes research undertaken to use computer technology in the analysis of aerial photographs of land resources.

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ABSTRACT

Environmental inventories of sites typically include some efforts to map land cover. These maps are used to describe the existing environment or to monitor and assess environmental changes. Digitized photo-analysis was investigated in this context for mapping vegetation complexes. The goal was to assess the utility of this technique for site analysis by testing several variables.

Seventy-millimeter color infrared transparencies of upland and lowland surface-resource complexes were digitized with a drum-type scanning microdensitometer. The effects of seasonal change and resolution on digital spectral signature behavior were investigated along with spectral signature extendability, classification accuracy, and time and cost efficiency of resource classification. Seasonal studies indicated that, for digital analysis, at least some spectral signatures were confused in all seasons, but these overlapping signatures shifted through the growing season such that a combination of seasonal data would successfully separate nearly all resources. As the resolution cell increased in size from 0.275 m^2 to 14.59 m^2, the spectral range of resource signatures decreased in width and became more discrete; however, linear resources such as roads were unresolved with the largest resolution cell. Signatures appeared to be extendable from image to image if images were from the same roll of film, were processed in the same way, were exposed within a short time span, were corrected and calibrated identically, and were scanned at the same time. The best classification accuracy achieved was 85% correct for two kinds of classifiers: one defined spectral resource signatures with a box-like configuration, and the other with an elliptical configuration. A basic parallelepiped (box-like) classification, including ground verification surveys, of a scene containing about 100,000 pixels cost approximately $100 and expended 20 h. A more sophisticated elliptical table look-up classifier, with various data transformations and enhancements, takes no additional time, but can increase the cost by $50.

Some images were successfully classified, but other classification attempts were abandoned; digitized film analysis was not an entirely reliable mapping technique. Resource signatures often overlapped. Additional research should determine if multiseasonal data overlayment, data-enhancement transformations, and machine adjustments can create the necessary reliability for operational applications.

This report was prepared with the cooperation of faculty and graduate students in the Department of Civil and Environmental Engineering at the University of Wisconsin-Madison.

Most of the funding for the research reported here was provided by the U.S. Environmental Protection Agency. Funds also were granted by the University of Wisconsin-Madison, Wisconsin Power and Light Company, Madison Gas and Electric Company, the Wisconsin Public Service Corporation, and the Wisconsin Public Service Commission. This report is submitted toward fulfillment of Grant No. R803971 by the Environmental Monitoring and Data Acquisition Group, Institute for Environmental Studies, University of Wisconsin-Madison, under the partial sponsorship of the U.S. Environmental Protection Agency. The report covers the period 1 July 1975 to 1 July 1977, and work was completed as of 31 July 1977.

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SECTION 1

INTRODUCTION

Since environmental impact assessment has become a requisite for many large-scale works, such as power plant construction, the need for efficient techniques to inventory natural resources of site environs has arisen. Ground surveys are usually used to obtain data that describe the environment of some proposed action. Ground-based resource surveys, including vegetation quantification and description, are typically laborious, time consuming, expensive, and often inconvenient for remote or hazardous study areas. The ability to inventory resources such as vegetation from a distance (i.e., to sense them remotely) avoids problems stemming from ground hazards or inaccessibility. For some data requirements, remote sensing may provide an improved means of data collection. Remote sensing with medium-scale (1:10,000 to 1:40,000) aerial photography provides rapid collection of immense amounts of data, a unique overview, good geometry and resolution, and powerful versatility. Although remote-sensing techniques have been applied to many survey problems, surveys of vegetation are among the most common applications.

Qualitative manual photointerpretation is the typical remote-sensing approach to surveying vegetation. However, quantitative data are often desired. Digitized film analysis, the subject of this study, automatically provides a quantitative assessment of ground resources. Digitized film analysis involves quantifying the spectral signatures of ground resources (vegetation types, water, roads, etc.) by measuring the dye densities of film with a scanning microdensitometer. After calibration and correction of the digitized film data, the resources can be characterized and classified based on their spectral signatures.

The specific intention of this study was to determine the versatility, accuracy, and cost efficiency in terms of time and money of digitized film analysis for mapping vegetation complexes. In addition to studying the general nature and capabilities of these classification procedures, we explored the behavior of individual resource signatures in response to seasonal change and changes in resolution.

Medium-scale (1:11,500 to 1:38,200) color infrared imagery was used for this study. The images portrayed complex lowland and upland scenes including various native and cultivated plant communities and structures (roads, dikes, buildings, etc.). The complexity of intermingled resources was intended to test severely the discriminatory power of digitized film analysis. The scenes were considered representative of nearly any site that may require an environmental inventory. The study areas ranged in size from several hundred acres.

SECTION 2

CONCLUSIONS AND RECOMMENDATIONS

Medium-scale color infrared images portraying complex upland and lowland resource scenes were digitized with a scanning microdensitometer. These scenes were considered representative of nearly any site requiring environmental inventory, including cover mapping. Computer analysis employed a software package developed by personnel of the Institute for Environmental Studies, Environmental Monitoring and Data Acquisition Group, at the University of Wisconsin-Madison (EMDAG). This study investigated the effects of different-sized ground resolution cells (pixels) and seasonal variation on resource spectral signatures and their separability for classification purposes. Further studies determined the extendability of resource signatures within a roll of film, the time and money expenses for a typical classification effort, and the degree of accuracy to be expected from such efforts.

Picture elements (pixels) with ground areas ranging from 0.275 m^2 to 14.59 m^2 were used to study the same resource scene. As the ground area represented by one pixel was increased, the spectral resource signature narrowed and the resource signatures became more discrete. Also, the reduction of the amount of data increased processing efficiency. One adverse effect of increasing the size of the pixel was the loss of resolving power; at the largest pixel size, linear features such as roads and dikes were difficult to discern. Also, the proportion of "edge" pixels (border pixels whose values represent an average of multiple resource signatures) increased compared to pixels representing single resources. The largest sized pixel (14.59 m^2) seemed slightly too large because of resolution problems, and the next smaller pixel (3.65 m^2) resulted in suboptimal signature separation; a pixel size near 10 m^2 would have been best. The choice of pixel size depends on the detail desired.

Seasonal variation of digital signatures was considerable, but over a growing season nearly all resources could be distinguished from one another. However, there was no optimal season for digital analysis. As might be expected, infrared reflectance increased from early spring into the climax of the growing season. Although the predominant red tones in mid- and late summer made manual interpretation more difficult, the degree of confusion among digital signatures remained fairly constant. An important result of this part of the study was the realization that at different times of the growing season, resource signatures shifted such that nearly all resources were distinct from one another in a temporal series. If multidate data files were overlaid and registered, a powerful classification could be developed, probably for little additional expense.

An important factor in the comparison of digital processing and manual interpretation was the extendability of resource signatures. For images of different scenes, at the same scale, from the same roll of film, exposed within a short time span, processed the same way, and digitized with like calibrations, cultivated resources (corn and alfalfa) had nearly identical respective signatures, whereas signatures of natural vegetation associations differed slightly more. With little modification the resource signatures could be generalized from one image to the other. Another aspect of this study was whether signatures could be standardized for data collected under different conditions. Again, for cultivated crops the relationship seemed stable when a simple ratio of signature means was used; however, this method proved very inaccurate when applied to a natural vegetation complex such as a woodland. The classification accuracy attained by applying these generalized signatures is worthy of further study.

A basic digital classification (simple parallelepiped classification without data enhancements) cost nearly $100 and consumed approximately 20 h for a single 70-mm film image. A more sophisticated classification can cost up to $150. These figures include all manual interpretive efforts, ground truthing, and iterations of computer runs, but do not include salaries.

If digital processing is compared with strictly manual interpretation, the comparative cost advantage depends on the desired product. For a single image where nonquantitative classes are needed, manual interpretation is probably superior. If resource signatures are generalized successfully for multiple images, an economy of scale favors digital processing over manual interpretation of multiple images. This economy depends on the areal coverage of the film imagery, that is, the scale. Quantification of the areal extent of a complex but distinct set of resources also favors digital analysis, even for a single image. The reliability of a basic digital analysis, without data enhancements, however, may influence the efficiency of a digitized approach compared to a manual approach. Some of the scenes analyzed had enough confused resource signatures to render those classification attempts futile. Data enhancements might have corrected the situation, but time was insufficient to experiment further.

The overall accuracy of the classifiers was lessened by a few complicated resource signatures, for example, woodlands. The accuracy including the problems incurred by woodland signatures was about 75% for the parallelepiped classifier, but, discounting the woods, an accuracy of better than 90% was achieved. For an elliptical table look-up classifier, the accuracy was 72%; nearly 80% of the misclassified pixels were due to trees.

The accuracy of the classifications was also tested after erratic pixels had been removed by using a smoothing routine. The result was that overall accuracy was improved to nearly 85% for both the parallelepiped classifier and the elliptical classifier.

Most confusion in all classifications was between upland and lowland resources. Little trouble was encountered distinguishing among upland resources or among lowland resources by themselves. Most of the accuracy problems were attributed to two facts: (1) the season was favorable for

classifying some resources while unfavorable for classifying some others, and (2) the scene was highly complex with intermingled signatures. A high level of detail was attempted. Analysis of scenes with a less complex resource base or use of a simple classification scheme, or both, would probably achieve greater accuracy.

Further studies could be directed toward improving the efficiency, reliability, and accuracy of digitized film analysis. The efficiency of this technology would be enhanced by incorporating into the process a better visual medium than paper printout, such as a color terminal. The extendability of signatures should also be further investigated. Accuracy and reliability may be improved by developing the ability to overlay and register multiseason data. Also, assembling the best data files obtained from various transformations and enhancements into one multiband data file might provide a basis for improved classification.

SECTION 3

LITERATURE REVIEW

Low-altitude medium-scale (1:10,000 to 1:40,000) imagery is an integral part of many land-related studies, e.g., soil mapping (Bushnell 1932, Baldwin et al. 1947, Kuhl 1970), land-cover or land-use classification (Colwell 1968, Nunnally and Witmer 1970), forest management (Spurr 1960, Avery 1966), geology (Lyon 1969, Cole and Owen-Jones 1974), and geography (Simonett 1969). The results of such studies may include quantitative tabular estimates of land-cover classes or some map product. Interpretation of low-altitude air photographs largely employs manual techniques with or without visual enhancement. The basis of interpretation is commonly qualitative ocular estimation (Anson 1968).

The development of film densitometry, coupled with the digital computer, allows quantification, storage, and management of enormous film-dye density data sets (Moore et al. 1964, Colwell 1965, Doverspike et al. 1965, Hoffer et al. 1972). Suitable algorithms can be applied to the data for purposes of correction, transformation, and enhancement (Smedes et al. 1971, Scarpace and Voss 1975, Berry and Smith 1977, Carter and Gardner 1977).

The advantages of digital film analysis include objective comparisons, signature extrapolations, quantification of resource signatures and areal coverage, economy of scale, and the aforementioned ease of data management and retrieval (Carter and Gardner 1977). Disadvantages are encountered with overlapping resource signatures and resources having complex textural patterns that are often readily identifiable to the eye (Whitman and Marcellus 1973), but extremely complicated for computer analysis (Wiersma and Landgrebe 1976). Registering picture elements (pixels) from the densitometer output to the original imagery can be difficult (Bernstein 1976). Additional problems arise, as with many mechanized processes, from machine (densitometer) maintenance and calibration procedures. These latter problems are largely surmountable and unrelated to theoretical concepts of densitometry. They should not detract from the potential of digital film analysis, but at any time they can hamper, halt, or invalidate an interpretive effort. Furthermore, some effort must be expended to gain a working knowledge of the computer hardware and software. The state of the art is developmental and dynamic. At present, the technology is not standardized and packaged such that potential users (resource planners and managers) could simply and immediately plug into a digital film-analysis system. The potential utility and efficiency of this approach has yet to be fully explored.

Recent applications of digital film analysis largely relate to studies of vegetation resources. These include general classifications of land use and

terrain (Doverspike et al. 1965, Smedes et al. 1971, Owen-Jones 1977) and discrimination of general plant communities (Driscoll et al. 1974) such as forests (Akca 1971, LeShack 1971) and wetlands (Egan and Hair 1971, Scarpace et al. 1975). Additional vegetation studies have been directed toward agricultural cropland inventory (Williams and Aggarwal 1976, Kamat et al. 1977), plant productivity and biomass (Driscoll et al. 1972, Pearson and Miller 1972), and crop infestation and disease detection (Ali and Aggarwal 1976). The use of digitized film for land-resource-management considerations was explored by Reppert et al. (1969) in regard to wildland sites, and by Benson et al. (1973) for soil limitations. Bryant and Zobrist (1976) and Cox et al. (1975) discuss a digital image processing system for overlaying geographic information for resource management.

SECTION 4

METHODS

SELECTION OF IMAGERY

Testing quantitative film analysis required the selection of suitable study sites with existing aerial imagery. To test fully the discriminatory power of digital film analysis, emphasis was given to scenes with very diverse and complex collections of resources. Multidate and multi-altitude imagery taken with a Hasselblad 70-mm format camera and 40-mm focal length lens was commissioned for the study of the Columbia Generating Station near Portage, Wis. (Fisher et al. 1977). Scales ranged from 1:11,500 to 1:38,200. This imagery included 70-mm transparencies of a scene containing a wide variety of lowland and upland resources (Figure 1a). Present in the scene were upland mixed oak woods, lowland aspen woods, dry prairie, structures (roads, dikes), deep sedge meadow, shrub carr, cattail (Typha sp.) beds, and floating duckweed beds.

Single-date imagery was also available for several similar scenes in the Madison, Wis., vicinity (Figure 2). These scenes included Hook Lake (Figure 1b), an acid sphagnum bog with zones of tamarack (Larix laricina) and leatherleaf (Chamaedaphne calyculata) over a sphagnum (Spagnum sp.) mat, wiregrass sedge (Carex lasiocarpa), and cattail surrounded by woods and agricultural fields; Waubesa Marsh (Figure 1c), a calcareous shallow wetland with much shallow sedge meadow, cropland, upland mixed oak woods, and constructed resources; and Waunakee Marsh (Figure 1d), an extensively disturbed wetland dominated by cattail and some shallow sedge meadow, and surrounded by cropland and upland mixed oak. Curtis (1959) thoroughly describes the flora and phytosociology of the various plant associations depicted on this imagery.

DENSITOMETRY

Transformation of multi-emulsion imagery into digital form can be accomplished by using a scanning microdensitometer. The photographic scanning for this study was performed with an Optronics P-1700 scanning microdensitometer, a revolving drum-type device that measures film-dye density with square pixels having linear dimensions of 25, 50, or 100 μ. Narrow-band filters are placed in the densitometer's light path to extract data for individual color layers of the multi-emulsion image. The output of the scanner is a two-dimensional array of numbers ranging from 0 to 255 proportional to the dye density. These numbers are written as 8-bit words on magnetic tape. For this study blue, green, and red filters having 100-Å band widths (centered at 4,500, 5,500, and 6,500 Å, respectively) were used

Figure 1a. Columbia Generating Station study area near Portage, Wis., April 1977.

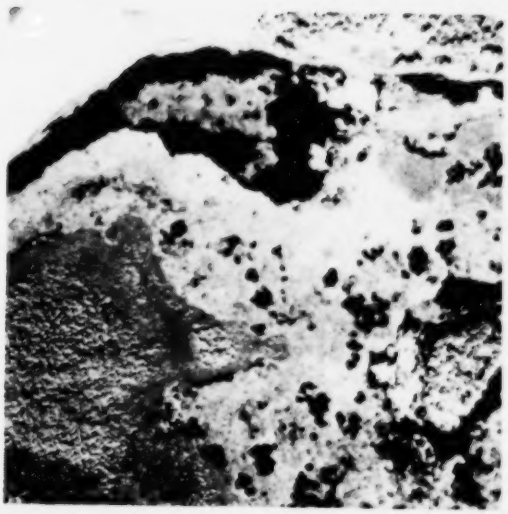

Figure 1b. Hook Lake study area near Oregon, Wis., October 1976.

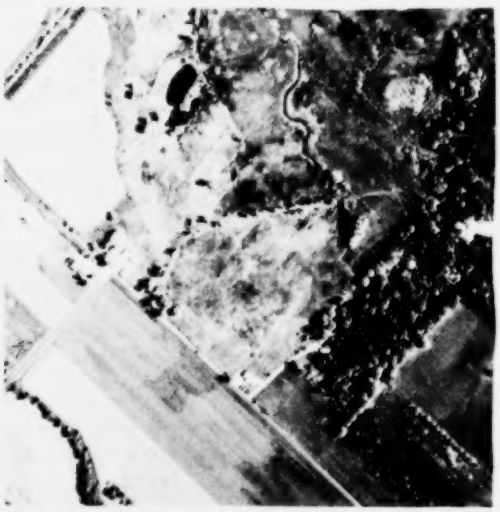

Figure 1c. Waubesa Marsh study area near Oregon, Wis., October 1976.

Figure 1d. Waunakee Marsh study area near Middleton, Wis., October 1976.

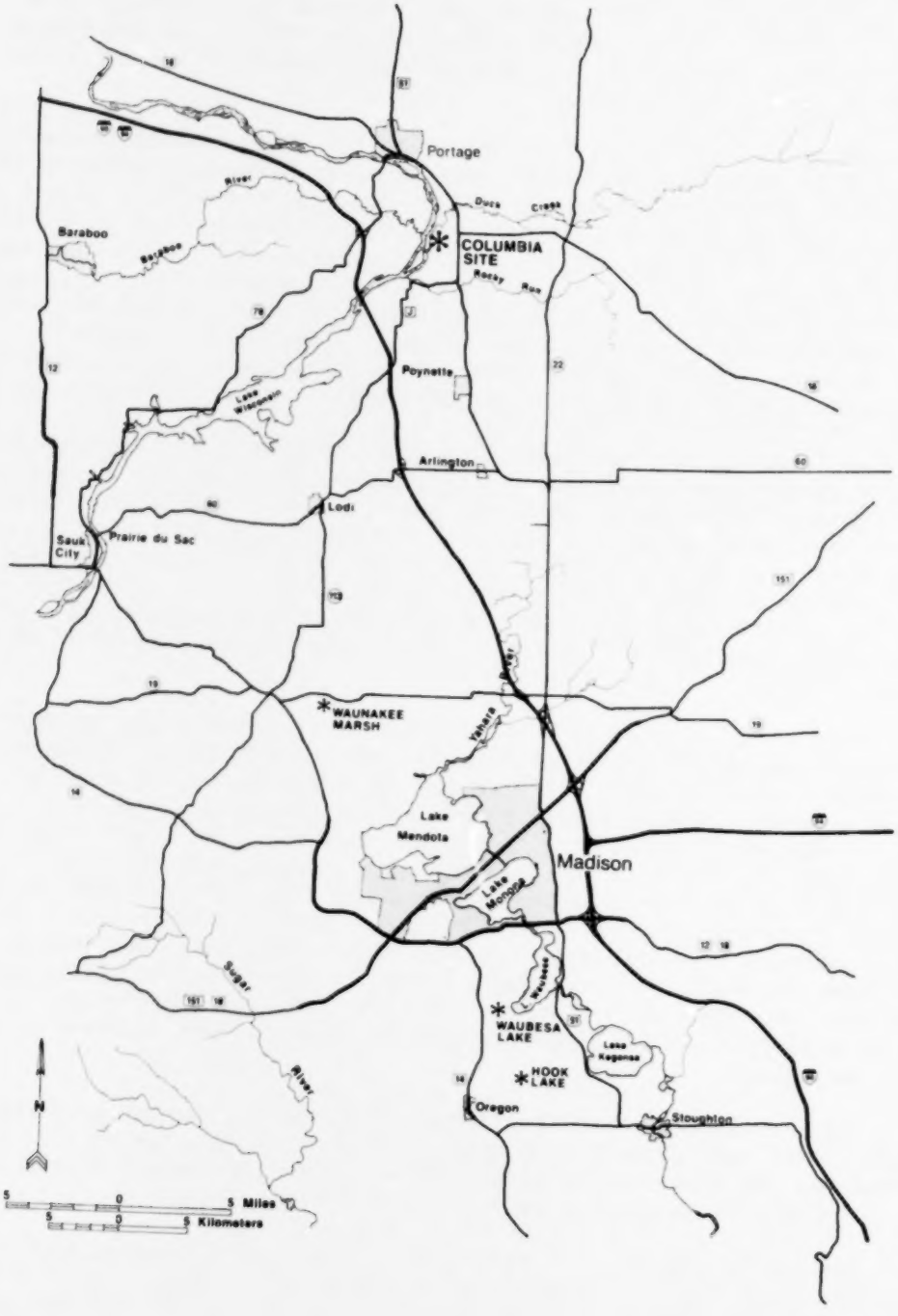

Figure 2. Location of study areas in the vicinity of Madison, Wis.

successively to create three raw data files for each image. By convention, the data files for the blue, green, and red bands were labeled bands 4, 5, and 6, respectively. The mechanical design of the scanner and the nature of multi-emulsion film resulted in precise registration of the three data files to within 2 μ.

Before the data can be enhanced or manipulated, several correction calibrations should be performed (details of sensitometric corrections and theory are discussed in Scarpace 1977). Because film density is not simply related to light reflected from the ground, reliance on such an assumption may cause problems (Scarpace 1977). Two main considerations affecting the use of film density are: (1) the actual relationship between film exposure and the resulting film density; and (2) the change in effective exposure on the film plane due to lens geometry. These effects, along with atmospheric interference, lens flare, and changes in ambient light, should ideally be compensated for before launching an interpretive effort (Steiner 1972).

The first step in the correction process is to plot the relationship of density versus exposure (ergs/cm^2) to obtain what is called a characteristic curve (Figure 3). This relationship which depends on film type, emulsion number, and, most important, the film processing, is derived by exposing a portion of film to a sequence of known fixed-energy steps. The developed film gives the investigator an incremental scale of densities, each with a known exposure. After this film wedge is digitized, the characteristic curve can be generated. Film wedges were available for all but the September imagery used in this study.

After the relationship between overall film density and exposure has been discerned, corrections for the behavior and interaction of the three dye layers and the film base for color and color infrared films must be applied. Any density measurement reflects the combination of all film layers. All layers contribute to the density because they have broad band sensitivities. If the specific spectral dye densities are known, the actual amounts of dye in each layer can be deduced after scanning the film through three narrow band filters (Scarpace 1977). After correction calibrations, a narrow band representation of the imagery can be derived similar to data from a multispectral photographic effort. Ideally, after the correction process, the data will have nearly the radiometric fidelity of an electro-optical scanner (where reflected energy is electronically measured) and the geometric fidelity of a photograph.

Additional corrections to compensate for problems such as darkened film edges due to lens falloff were not operational at the time of this study. Therefore, the study scenes were selected as much as possible from the center of their respective images, away from the darkened edges.

Several algorithms were available to transform, enhance, and separate the resource signatures in the data files. Three transformations were used most commonly in this study. (1) The ratio of one band to another was completed. The result was a band in which aberrant values caused by variations in scene illumination were removed (Goodenough and Shlien 1974). (2) Canonical discriminant analysis transformed data into new "pseudo-bands" oriented so

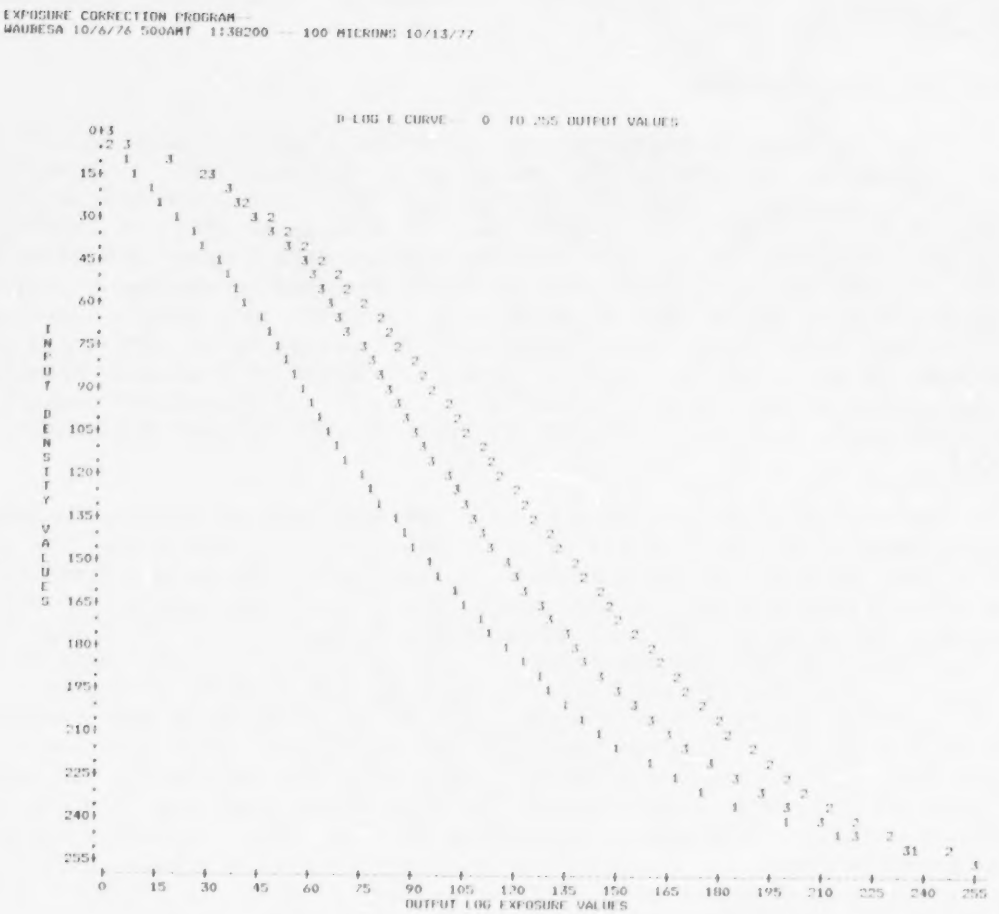

Figure 3. Characteristic curve (density versus log $_{10}$ exposure) of corrected dye densities for blue, green and red dye layers of color infrared film.

that the separation of specified resource signatures was maximized. (3) Texture characteristics were elucidated by computing the standard deviation of each pixel and its neighboring pixels within a specified distance. Areas with highly contrasting textural patterns produced higher standard deviations. An additional file was created for this information. The texture algorithm was the only transformation used for final classifications.

COMPUTER CLASSIFICATION

After an image is digitized and corrected, representative sets of pixels are selected so that the surface resources in the scene can be classified by computer. To achieve these classifications each pixel's spectral signature is compared to the signatures of known sets of pixels, selected to represent as nearly as possible all surface resources in the data (Wacker and Landgrebe 1972). These "training sets" are carefully selected to represent single "pure" resource signatures. Complexes of resources in a single training set will result in confused classifications. The selection of pure training sets becomes the most critical part of these classification processes because training-set signatures are the defining factors. A supervised computer classification is only as good as the training sets (Wacker and Landgrebe 1972).

The encoding of training sets is a two-step process relying on knowledge of the separation and identity of the resources in a given scene. In the first step each of the three data files containing single-band pixel values can be assigned a string of characters to represent increments of pixel values. For example, if the blue-band data file contained pixel signature values from 1 to 255 and the character string "1 2 3 4 5" was assigned to represent all values in this file, a computer map could be generated in which all pixels in the file having values 1 to 51 are printed as the character "1", those from 52 to 103 are the character "2", and so on until all five increments are assigned a character. The vernacular expression for such a process is a density-level slice or contrast stretching; the file was sliced into five levels in this hypothetical case. The values in a file can be assigned any number of characters available from a line printer and, therefore, can be sliced into whatever number of levels is desired. An optional string of characters is an overprint string, which maximizes the contrast among levels on the output map. The darkest characters can be assigned to the highest or lowest signature values by preference.

Between 9 and 12 levels have been found useful in portraying the general patterns of resources on a digitized scene (Figure 4). The recognition of resource patterns on a level slice (such as water, corn fields, and trees in Figure 4), allied with prior knowledge of resources in the original image (usually attained with manual photointerpretation and ground truthing), allows delineation of training sets. Although the digitized scene can be presented by other methods, for example, by using color terminals or by selecting training-set coordinates (as with ground surveying and photogrammetry), all methods rely on the transfer of some knowledge of ground resources to the digitized scene.

Figure 4. Nine-level density slice of the green band from Hook Lake digital data file using overprint option.

The second step is to recognize and encode the row and column coordinates of the training sets. The available software allows odd-shaped training sets to be encoded simply by recording all the vertices. This feature of extracting general polygons can be an advantage over rectilinearly restricted sets (Heiber 1976). Some resources, especially woods, contain a multitude of signatures as one looks at crowns, edges, shaded depressions in the canopy, etc. (Kan et al. 1975). All such signatures must be recognized if a category "woods" is to be completely classified. The requisite training sets are often small, containing perhaps only four pixels. Since the statistics of a training set with only four members are unreliable, a program was developed to allow merging of training sets representing like classes and like signatures. Care was necessary to avoid mixing pure training sets with impure ones. Much positive effort can be negated by one such misfortune. For the complex scenes used in this study, 70 or 80 training sets were commonly designated in an initial effort to represent all resources present. Additional iterations needed to fill blank spots in a classification might require several more training sets.

Once training sets are identified and encoded, a program is run that extracts and files the signature information in each band for every training set. The signatures can then be presented as computer output in various forms so that judgments can be made as to their accuracy and adequacy. These forms include histograms (Figure 5), bar diagrams (Figure 6), and scatter diagrams (Figure 7). Each has inherent advantages and disadvantages.

The bar diagrams give the most rapid visual approximation of how resource signatures relate to one another and the extent to which they overlap. In such diagrams the mean of each signature is designated along with three standard deviations, and the spread or normality often indicates the purity of the signature. Since bar diagrams are not detailed enough to allow inference of specific spectral boundaries, they are best applied as an indication of data quality. If resources are seen to be badly confounded at this point, either the classification process can be abandoned or appropriate transformations can be applied to enhance the data.

Histograms are the usual mode of presenting resource signatures in sufficient detail to permit assignment of spectral bounds. With histograms the values in each band of every pixel in a training set can be viewed collectively, the goodness of fit to a normal distribution can be judged if enough pixels are present, and the number and degree of aberrant values are commonly evident. If multiple resources are inadvertently included in a training set, however, their respective signatures cannot be separated conclusively.

In such cases, when multiple-resource sets are suspected, scatter diagrams are best applied. Bimodal histograms for single bands are not very informative, but when pixel values from two bands are plotted, the extra dimension can successfully separate the resource signatures. The problem and its solution by using "scatter diagrams" is illustrated in Figures 8a and 8b.

After the quality and character of the signatures are discovered, several editing capabilities are available. In addition to being merged, training

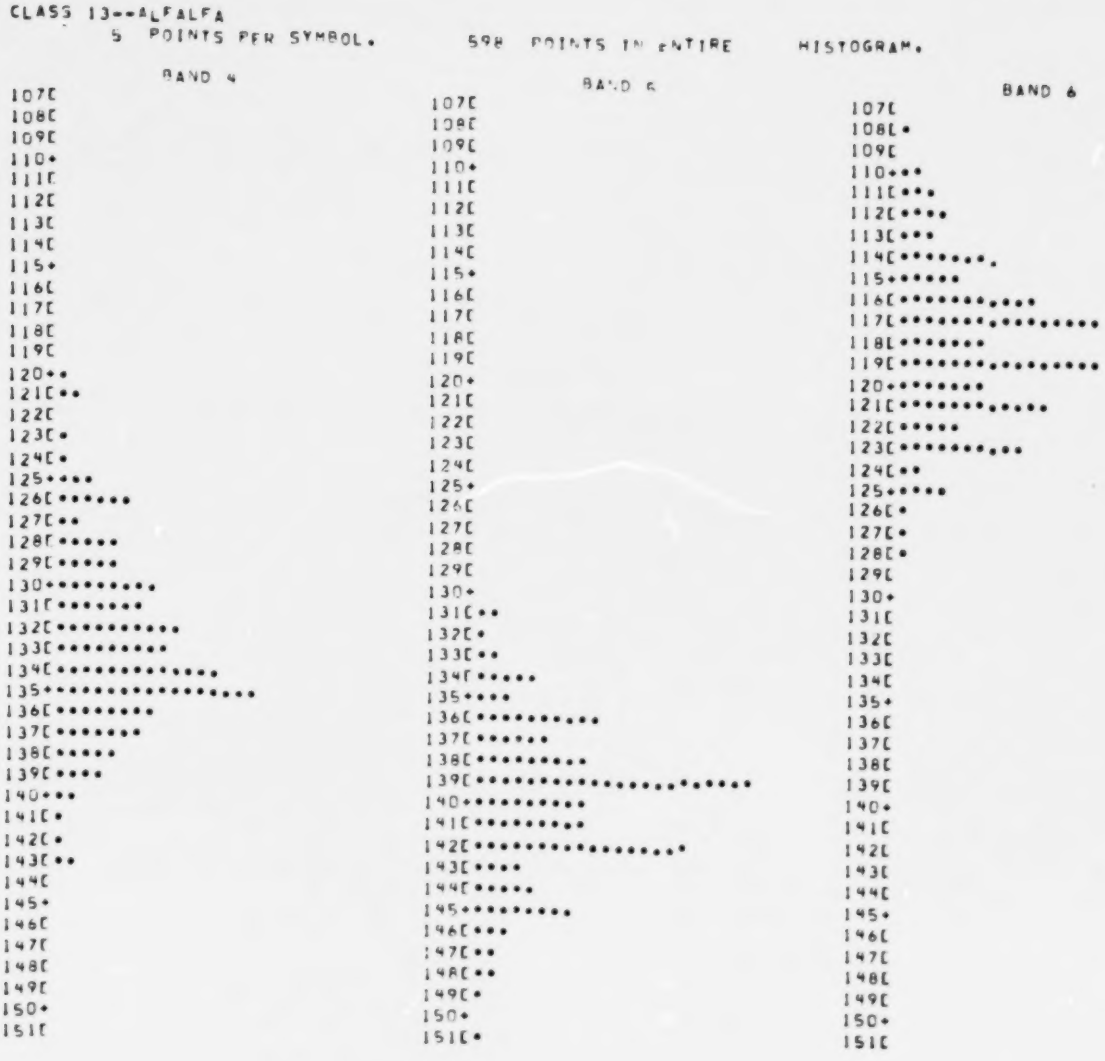

Figure 5. Example of a histogram display of information in a training set.

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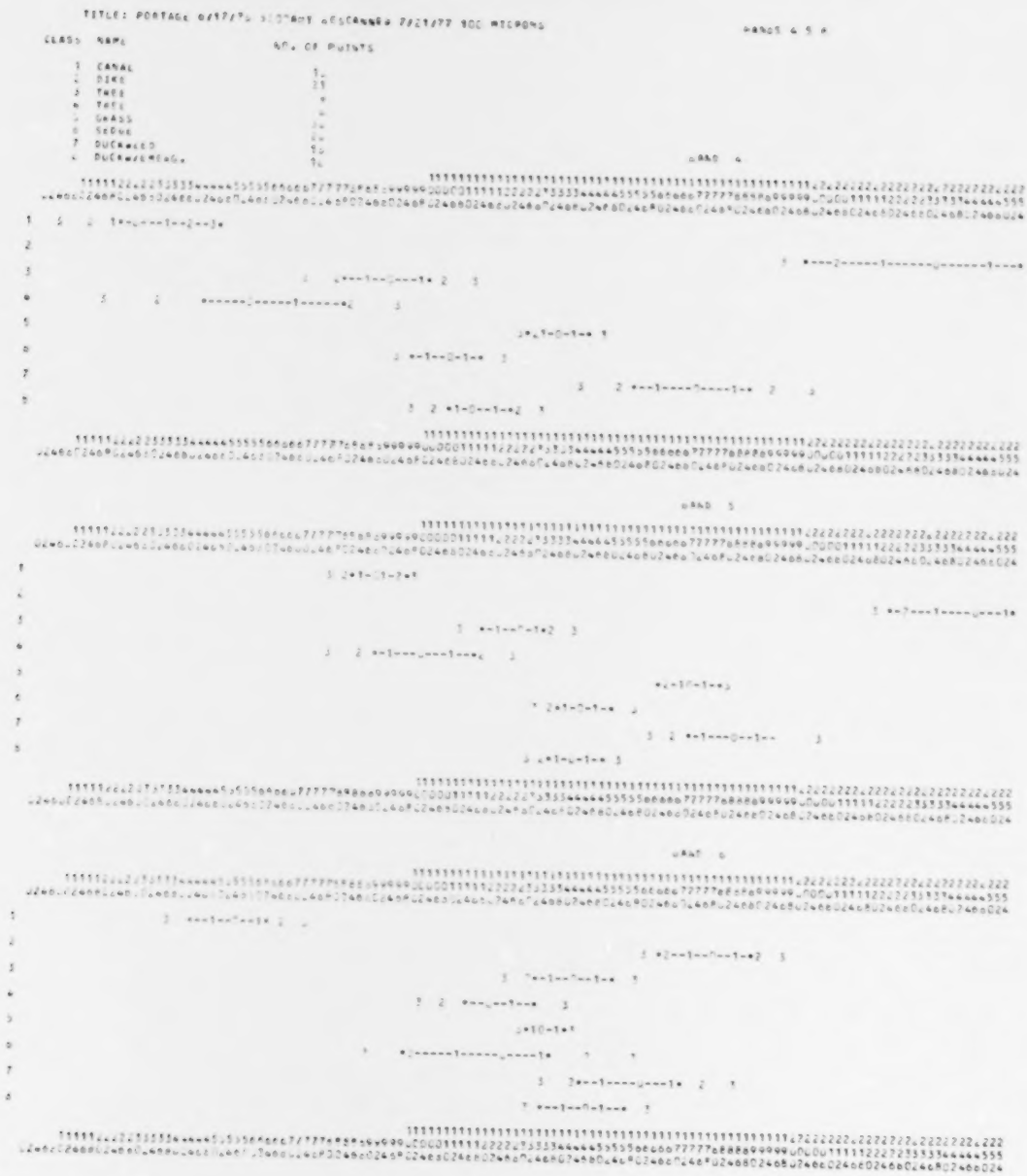


Figure 6. Example of a bar diagram display of information from several training sets.

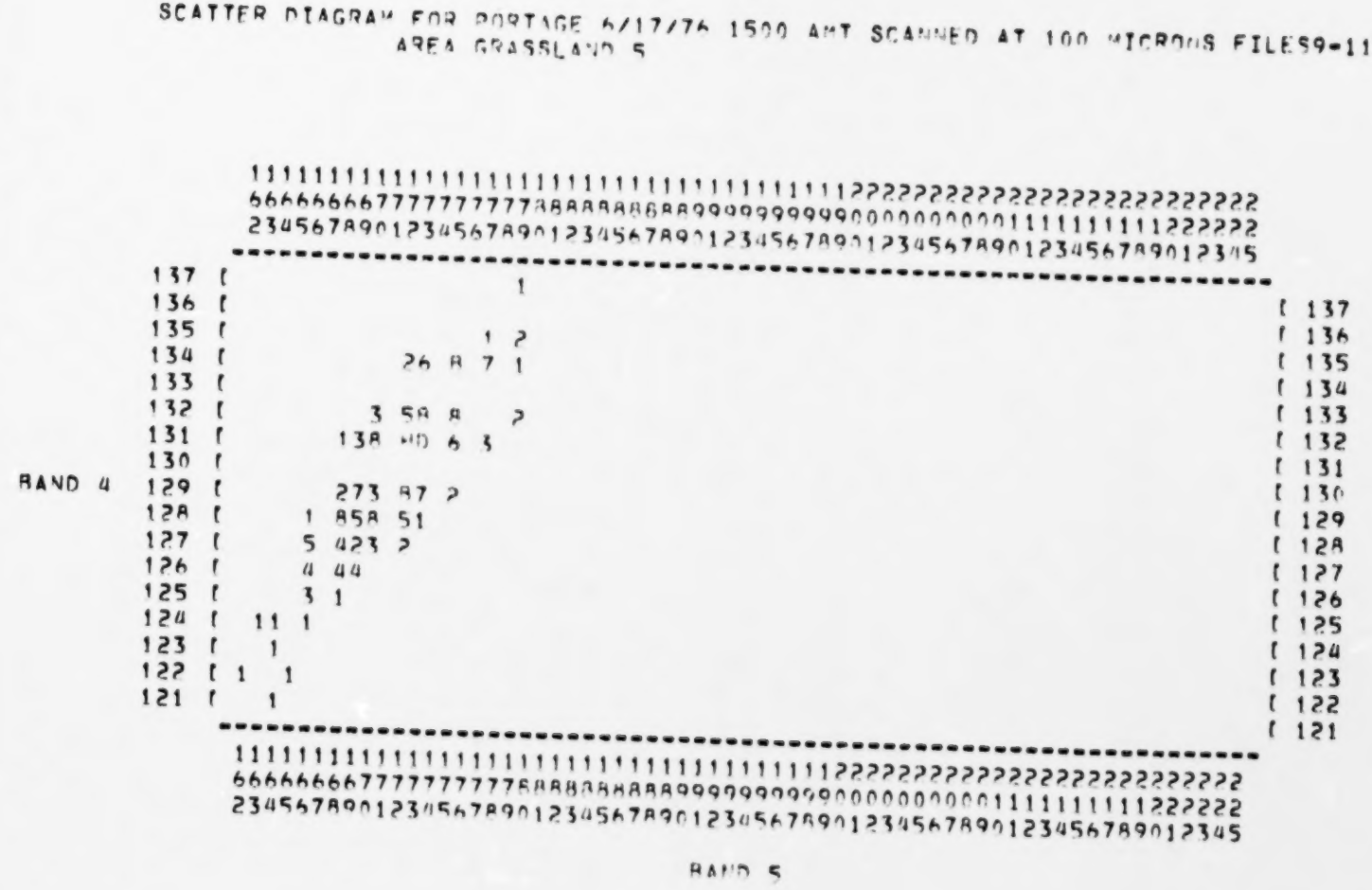


Figure 7. Example of a scatter diagram display of information from a training set in two bands.

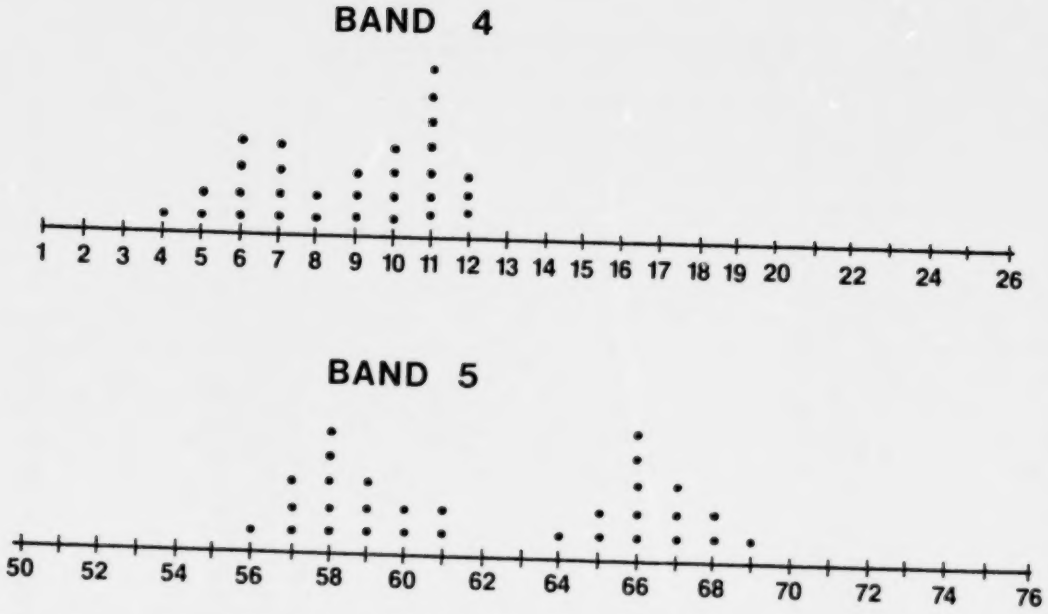


Figure 8a. Bimodal histograms showing two bands of information from a two-resource training set; individual resource signatures cannot be discerned.

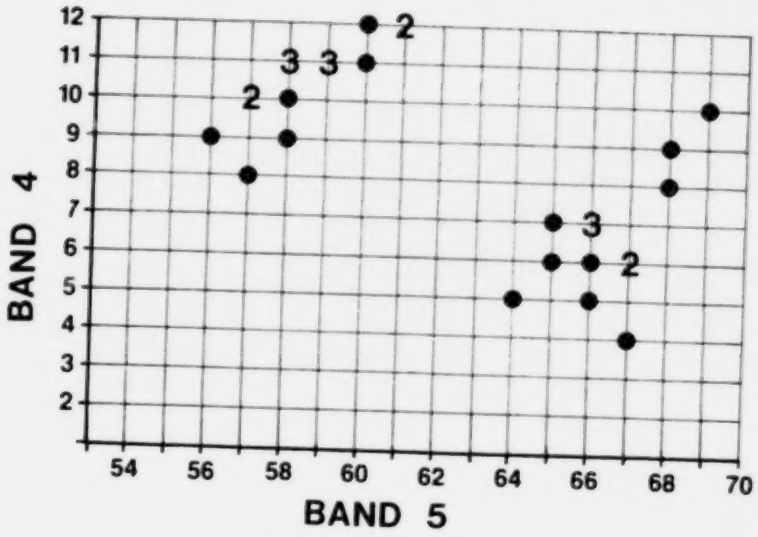


Figure 8b. Same resource signatures resolved by using scatter diagram of two bands.

sets can be deleted, identities changed, signatures trimmed to within a specified number of standard deviations, or arbitrary upper or lower bounds can be imposed on training-set signatures to remove outside pixels. As mentioned previously, extreme caution is recommended since useful information can be obscured or lost during these manipulations.

After signatures are satisfactorily quantified and displayed, a classification can be applied. Several types of classification algorithms exist. The simplest is a "parallelepiped" or "box" classification. Each resource class is assigned upper and lower bounds in each band. Thus, in three dimensions, a rectilinear set of boundaries defines each resource signature. All pixel values are tested against the boundaries for all bands. Those inside a given class parallelepiped are so classified. If a pixel does not fit into any box, it remains unclassified. This algorithm is simple and fast (Hyde et al. 1977). However, real signatures seldom occupy a box-like configuration. Instead, the signatures typically assume an elliptical configuration when plotted in two or three bands. Two signatures can actually be distinct, but a box classifier will still confuse them (Figure 9).

More sophisticated classifiers rely on the statistics of the training sets and data points. Computer programs are available that provide standard statistics such as mean vectors, eigenvalues, eigenvectors, and covariance matrices for each resource. An ellipse can be defined for each resource, and an array of these definitions can be loaded into a tabular file based on these statistics. Classification decisions can then be achieved by "looking up" these elliptical definitions in the table and comparing pixel values to them. This table look-up or elliptical classifier was used in this study alternately with the box classification. Both assume a Gaussian distribution of signature pixel values.

Various other classifiers exist that were not employed in this study. Most make use of some minimum distance or maximum likelihood rule whereby individual pixels are classified according to the statistics of resource spectral signatures or vectors that associate most closely. These are the "vector-by-vector" classifiers as described by Wacker and Landgrebe (1972). The expense of these semi-automatic or fully automatic classifiers is greater than for those used in this study because of the comparative calculations required for every pixel in the vector-by-vector approach (Hyde et al. 1977).

Classifications can be put out as color television displays, film images, or line-printer maps. The assignment of characters or colors to each class is arbitrary; the original scene can be altered or enhanced, or both. This study employed both line-printer maps (Figure 10) and digitally reconstructed film images (Figure 11) to present finished classifications.

TEST VARIABLES

This study identified five major variables requiring investigation. They were selected on the basis of their anticipated importance in a problem-solving situation involving resource inventory or classification.

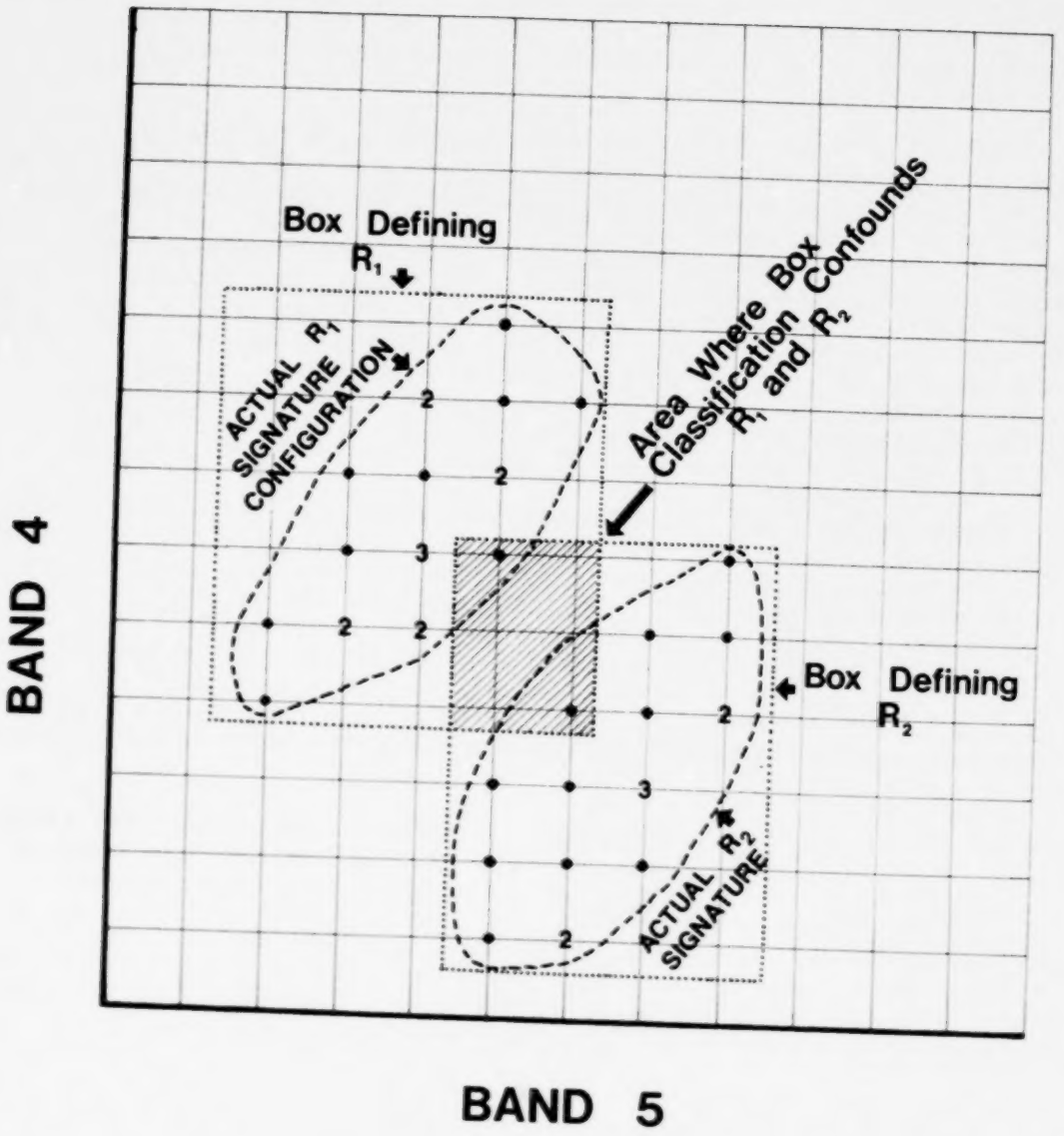


Figure 9. Illustration of two discrete elliptical resource signatures and their confusion by a parallelepiped definition.

TITLE: PORTAGE 4/26/77 1:19100 2500AMT SCANNED AT 100 MICRONS 8/3/77
TAPE READ RESOLUTION: 1 PRINT RESOLUTION: 1
START ROW: 1 END ROW: 132 START COLUMN: 4 END COLUMN: 123

TITLE: PORTAGE 4/26/77 1:19100 2500AMT SCANNED AT 100 MICRONS 8/3/77
TAPE READ RESOLUTION: 1 PRINT RESOLUTION: 1

CHARACTER	RESOURCE	BAND	LOW	UP	BAND	LOW	UP	BAND	LOW	UP		
#	WATER-SHADE	4	0	28	5	50	76	6	0	6	NUMBER OF PIXELS FOR WATER-SHADE	470
#	WATER-SHADE	4	40	76	5	86	107	6	0	60	NUMBER OF PIXELS FOR WATER-SHADE	1255
#	WATER-SHADE	4	15	43	5	68	87	6	0	10	NUMBER OF PIXELS FOR WATER-SHADE	84
Y	TREE1	4	88	126	5	112	148	6	55	98	NUMBER OF PIXELS FOR TREE1	4738
Y	TREE2	4	78	103	5	96	122	6	68	105	NUMBER OF PIXELS FOR TREE2	515
Y	TREE 3	4	59	76	5	80	105	6	43	90	NUMBER OF PIXELS FOR TREE 3	335
#	SHADE	4	5	47	5	54	80	6	0	58	NUMBER OF PIXELS FOR SHADE	163
*	GRASS	4	118	145	5	146	168	6	58	86	NUMBER OF PIXELS FOR GRASS	2879
*	GRASS	4	100	139	5	117	161	6	59	105	NUMBER OF PIXELS FOR GRASS	3105
.	SAND	4	152	220	5	178	236	6	90	136	NUMBER OF PIXELS FOR SAND	568
Y	TREE-SHRUB	4	79	103	5	123	147	6	49	67	NUMBER OF PIXELS FOR TREE-SHRUB	982
Y	TREE-SHRUB	4	50	100	5	88	126	6	36	66	NUMBER OF PIXELS FOR TREE-SHRUB	1610
S	SHRUB	4	126	154	5	154	176	6	68	94	NUMBER OF PIXELS FOR SHRUB	455
											NUMBER OF PIXELS UNCLASSIFIED	681

Figure 10. Example of line printer output of classification from the Columbia Generating Station study area, April 1977.

Figure 11. Example of film classification output from the Columbia Generating Station study area, April 1977. Green= grassland, orange = woods, yellow = sand and gravel, brown = water and shade, olive = shrubs.

Ground Resolution

The different altitudes resulted in imagery scaled at 1:11,500, 1:19,100, and 1:38,200. The scanning microdensitometer apertures were set at either 50 or 100 μ. This combination of image scales and scanner apertures provided essentially four different-sized ground resolution cells (Table 1).

TABLE 1. GROUND RESOLUTION CELL SIZES FOR DIFFERENT COMBINATIONS OF IMAGE SCALE AND SCANNER APERTURE[a]

	Scale		
Aperture (μ)	1:11,500	1:19,100	1:38,200
50	0.275/0.525	------	------
100	1.32/1.15	3.65/1.91	14.59/3.82

[a]Cell size = pixel ground area (m^2)/linear dimension of pixel (m).

The optimum ground resolution cell was studied first so that it could be used in subsequent portions of the study. Considerations in determining what constituted an "optimum" pixel size were: (1) preserving ground detail and accuracy, (2) reducing data to manageable proportion, (3) removing "noise" from the data, and (4) maximizing time and cost efficiency.

These goals obviously conflict. When compromise was required the decision as to how to optimize all constraints was bound to be subjective. For example, the desire to remove some of the textural noise from woods sometimes required a scale that would not resolve linear features such as roads. Is resolving roads more or less important than facilitating woods classification? This sort of question occurs constantly and can only be answered by individual investigators in the context of their needs. This study was directed toward ascertaining what pixel size resulted in roads being unresolved or woods attaining less noisy signatures.

Seasonal Variation

The study of seasonal variation used the same scene as the ground resolution study. Aerial photographs at a scale of 1:19,100 spanned the 1976 growing season from late May to late September on a monthly basis. An early spring image taken in late April 1977 was also analyzed. Relative resource spectral signatures were emphasized. Of special interest were how individual natural resource signatures change over the growing season, which resources were confounded, and what season, if any, was optimum for separating, classifying, and quantifying resources. Since vegetation resources are the most sensitive to seasonal variation, the rich variety of vegetation types in the lowland and upland areas was carefully scrutinized.

Generality Attributes

An important determination, which heavily influences cost and time efficiency, is whether the resource signatures on a given date can be generalized from one image to another, within the same roll of film, or among rolls. This factor is crucial because it determines whether the effort of identifying resource signatures must be repeated for every image analyzed. If signatures can be generalized, only new resources on additional scenes must be defined; previously identified resources can be classified by applying known signatures.

The signatures of selected resources were compared among film frames taken from a roll of film depicting the same vicinity on a single date. This test involved October imagery depicting Hook Lake, Waubesa Marsh, and Waunakee Marsh (Figure 1). The signatures of resources common to the three sites were compared. These frames were taken from the same roll of film, which had been exposed during a single flight.

This portion of the study was not limited to discerning whether like resources have like signatures. The possibility that signatures vary with some direct relationship was studied with the prospect that the relationship could be used to standardize signatures within a single-date roll of film.

Cost-Time Efficiency

Costs, in terms of time and computer-account money, were documented in a daily log for the entire classification process. The goal was to determine representative costs of processing an image from the point of digitizing to final interpretation. Many repetitions were recorded for each step in the process, including data enhancement and presentation. For excessively repetitive processes, most but not all iterations were documented.

On a more limited basis, the costs of ground-level interpretation and manual air-photo interpretation were explored. These methods, the two most common approaches to resource inventory, provided an important basis for comparing computer-interpretation expenses.

Accuracy

In addition to providing economic bases of comparison, the ground observations and manual photointerpretations act as evaluation techniques (Curtis 1977, Townshend 1977). Each resource scene was visited on the ground and manually interpreted for resource verification.

For more detailed comparisons, a mylar overlay was made of some magnified imagery, and resource patterns were traced thereon (Figure 12). These mylar maps were brought into the field where the delineated resources were identified and verified. Registration of the delineated resources to actual ground entities was accomplished largely by relying on landmarks. In most cases the entire area was quickly perused and attention was given to representative resource occurrences; once a resource's appearance was satisfactory, the identity was extrapolated to likenesses in the scene.

The manual techniques were assumed to result in nearly perfect knowledge of resource occurrence and identity. This knowledge was used to draw conclusions as to the accuracy of the digital analysis. A parameter of accuracy was calculated by selecting, with a random numbers generation, 200 pixel coordinates per scene (approximatly 0.2% of the total) and by determining the percentage of accurately identified pixels (Figure 13). The known proportions of resource classes were used as expected proportions for the 200 sample pixels. A chi-squared test was then applied to the sample proportions to see if the sample pixels were a fair representation of the original population. The results agreed with minimum sampling adequacy requirements for major resources put forth by van Genderen and Lock (1977). This overall percentage does not necessarily reflect the relative ease or difficulty of separating various individual resources. Some resources, such as pavement, nearly always classify easily. Some commentary is directed toward chronically confused resources, and a confusion matrix is presented for each classification.

Figure 12. Hook Lake resource map as manually interpreted and traced on a mylar overlay of 70-mm color infrared image (original scale 1:38,200 magnified approximately 6X).

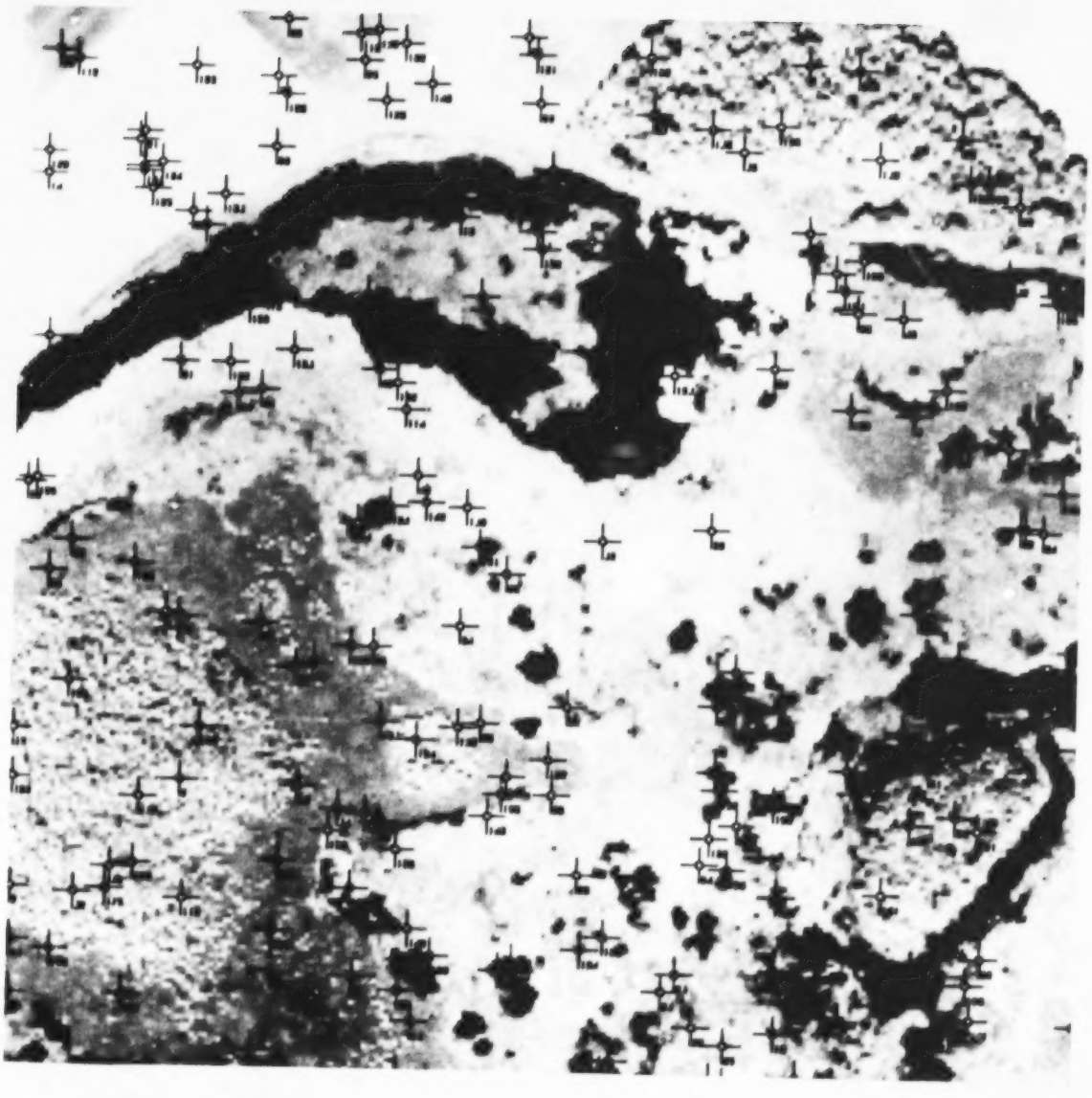


Figure 13. Randomly selected and marked pixels on digitally produced film image of Hook Lake study area for accuracy check.

SECTION 5

RESULTS AND DISCUSSION

GROUND RESOLUTION

This section explains the behavior of resource signatures in response to the application of four different-sized ground resolution cells; sizes ranged from 0.25 m^2 to 14.59 m^2. Images of the Columbia Generating Station site from mid-June 1975 were used. These images were photographed on a single flight with one roll of film. The altitudes above mean terrain level were 1,500, 2,500, and 5,000 ft. The signature behaviors of a few representative resources are presented in Table 2.

The spectral signatures for each pixel size are not perfectly symmetrical. Most of the variance was caused by a combination of the correction algorithm, training-set placement, densitometer idiosyncracies, phenology, and textural characteristics. Of these variables, training-set placement is the only one that the investigator can totally control. Therefore, unless the investigator is capable of redesigning the software and hardware, some variability in the data might be expected. Direct comparisons of signature data must be tempered with this consideration.

Although the mean vectors of the training-set signatures do not align perfectly, the signatures tend to narrow with increasing pixel size (Table 2). The average signature widths for each pixel size are 62.6 for 0.275 m^2, 55.4 for 1.32 m^2, 49.3 for 3.65 m^2, and 35.8 for 14.59 m^2 (Figure 14).

Considering individual resources, the average reduction in signature widths was 63.4% for grass, 50.8% for woods, 44.5% for sand, and 20.5% for duckweed. The differential signature improvement might be expected because of the relative extent of the resources. Woods and grasslands covered extensive areas, whereas sandblows and duckweed colonies were relatively small.

Reducing the ground resolution power served to average and smooth internal noise in the woods and grassland signatures. The expected improvement in the internal cell signatures of the smaller resources was probably balanced somewhat by the pollution of edge pixels (pixels overlying two resources and having a signature derived from an average of the reflectance of the two resources). For small resources the edge pixels are proportionally more influential; avoiding edge pixels while selecting training sets of small resources is difficult. The overall improved stability of resource signatures, however, is illustrated by the plot of signature standard deviations versus pixel size (Figure 15).

TABLE 2. SIGNATURE BEHAVIOR OF GRASSLAND, WOODS, SANDBLOW, AND DUCKWEED FROM THE COLUMBIA GENERATING STATION STUDY AREA, JUNE 1976, IN RESPONSE TO DIFFERENT-SIZED GROUND RESOLUTION CELLS

Resource	Band	Pixel	0 50 100 150 200 255
Grass	4	0.275	92–179
		1.32	116–142
		3.65	104–154
		14.59	118–144
	5	0.275	160–218
		1.32	158–190
		3.65	150–188
		14.59	154–180
	6	0.275	98–155
		1.32	150–180
		3.65	113–162
		14.59	130–152
Trees (a combination of three different tree signatures)	4	0.275	22–134
		1.32	51–105
		3.65	78–129
		14.59	64–120
	5	0.275	96–158
		1.32	75–126
		3.65	113–151
		14.59	112–148
	6	0.275	114–196
		1.32	138–192
		3.65	118–171
		14.59	118–154
Sand	4	0.275	186–255
		1.32	132–210
		3.65	160–236
		14.59	186–219
	5	0.275	236–255
		1.32	186–255
		3.65	192–255
		14.59	222–247
	6	0.275	159–208
		1.32	177–228
		3.65	142–190
		14.59	168–186
Duckweed	4	0.275	153–219
		1.32	110–184
		3.65	143–192
		14.59	136–184
	5	0.275	165–216
		1.32	136–210
		3.65	156–197
		14.59	154–194
	6	0.275	150–189
		1.32	144–216
		3.65	135–170
		14.59	136–170

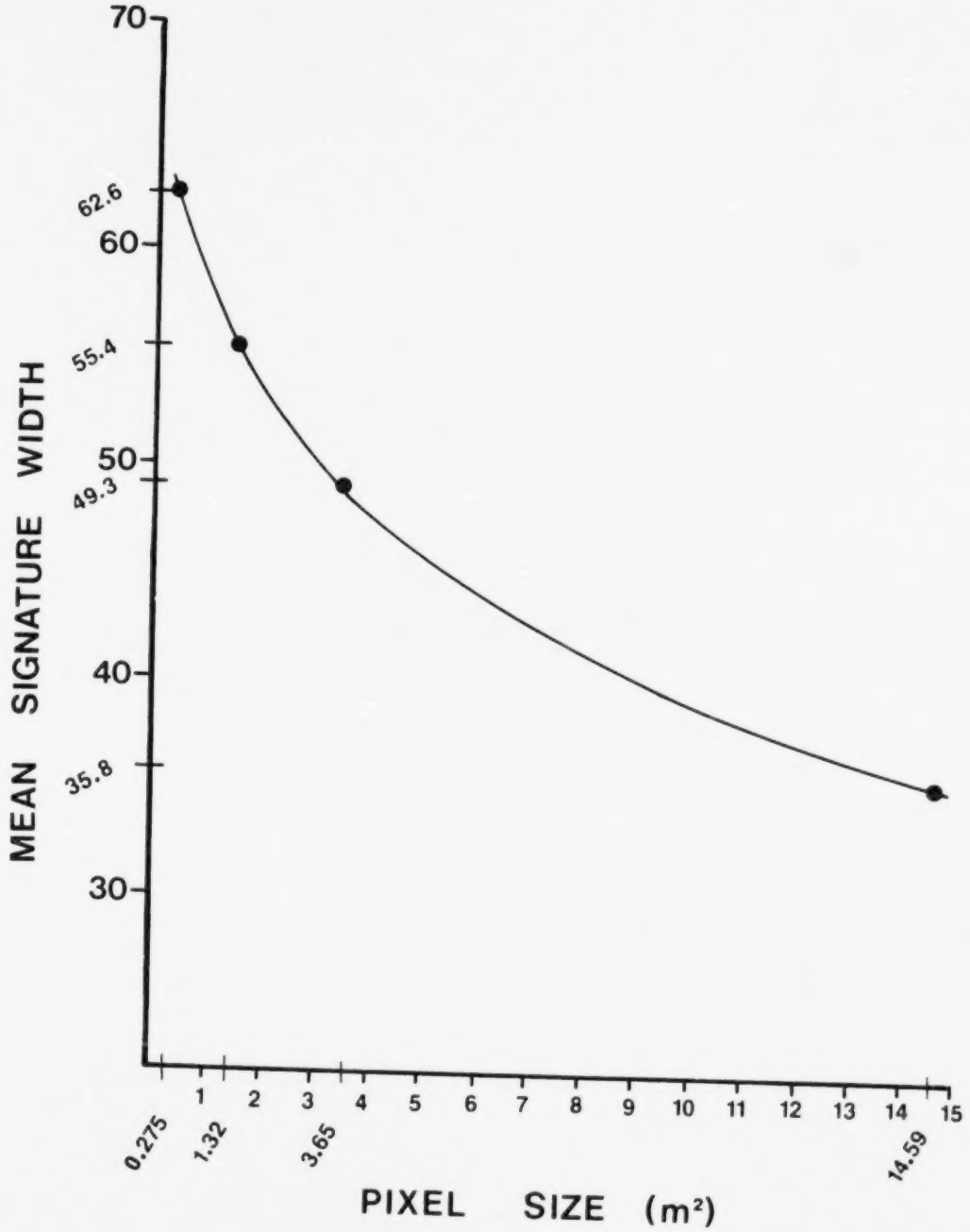


Figure 14. Relation between mean signature width (from Table 2) and ground resolution cell size. Data from three images of the Columbia Generating Station study area in June 1976 at scales of 1:11,500, 1:19,200, and 1:38,200, and scanning apertures of 50 and 100 μ.

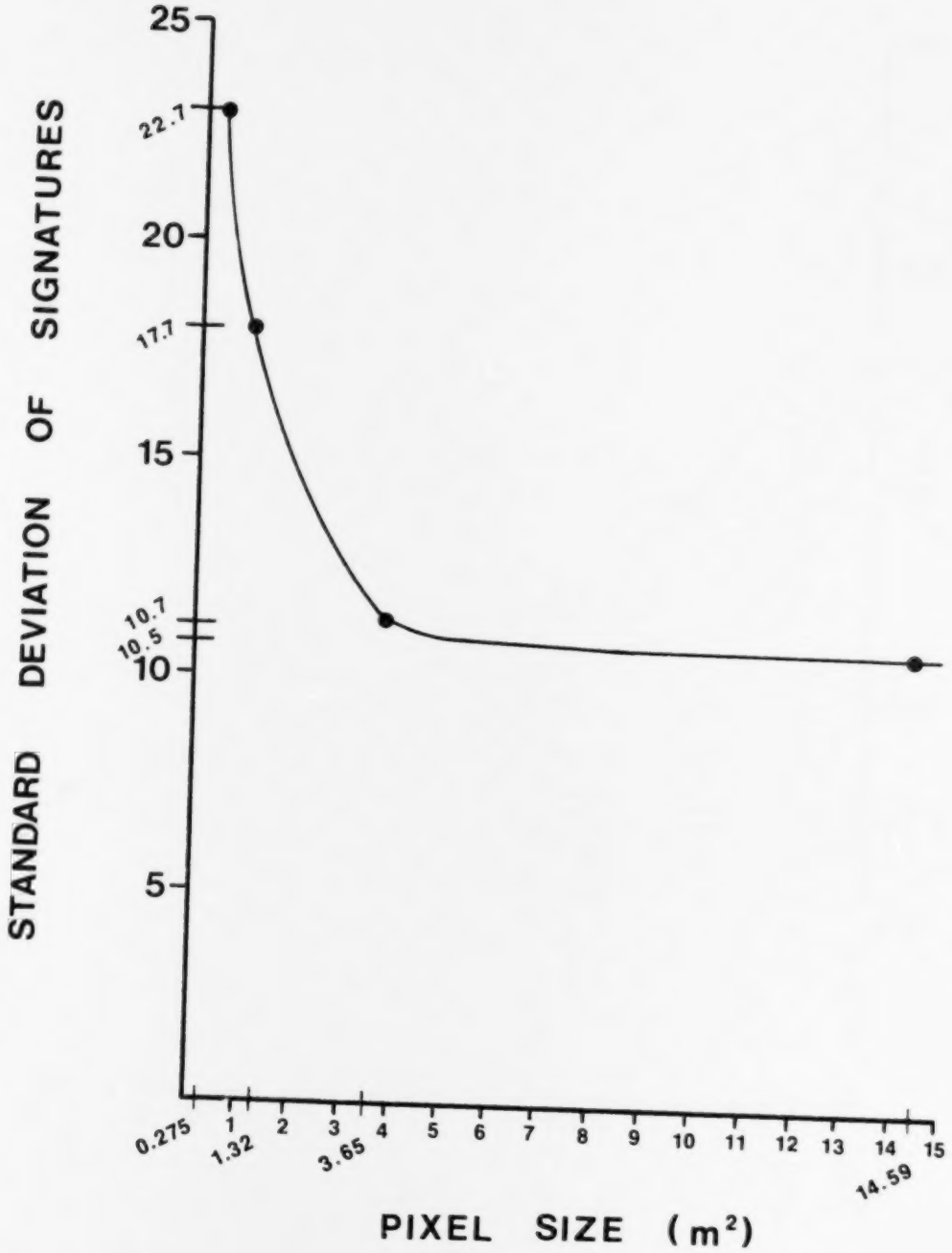


Figure 15. Relation between standard deviation of resource signatures (from Table 2) and ground resolution cell size. Data from three images of Columbia Generating Station study area in June 1976 at scales of 1:11,500, 1:19,200, and 1:38,200 and scanning aperture of 50 and 100 μ.

Reducing signature ranges is desirable in the attempt to achieve discrete resource classes. Since selection of pixel size is related to the discretion of signatures and to the amount of data available, this selection is an important consideration for digital analysis.

In addition to the need to achieve discrete resource classes, the other main criterion influencing a decision on pixel size is the need to resolve resources. Figure 16 illustrates the resolution success of a portion of the Columbia Generating Station study area with four pixel sizes. Grassland and woods border a sandblow in this scene. The configurations of the sandblow and individual tree crowns are very obvious when a 0.275-m^2 pixel is used. When the largest pixel is used, however, the edges of the sandblow become rough and angular; the shape is only approximately correct. The texture of the woods becomes increasingly smooth with larger pixel size. Although roads are not present in this scene, a resolving power sufficient for classification of roads less than 7.5 m (25 ft) wide is not attainable as the pixel size of 14.59 m^2 is approached. This is true for any resource having a similar minimum dimension.

As the pixel size increases, the number of pixels needed to represent a resource on the ground decreases. Therefore, the number of edge pixels increases in proportion to the pixels that purely represent a single resource. These edge pixels detract from a classification effort because they have irrelevant and erratic signatures. Coping with more edge pixels should be considered when deciding to increase pixel size.

An additional influence on choosing an optimum pixel size is the identification of the resources that are the main targets of the classification. Signatures of larger grossly textured resources are improved by increasing pixel size (Kan et al. 1975), whereas small resources may be unresolved. If these smaller resources are deemed critical, the smallest dimension of these target resources must be the standard for sizing the pixel.

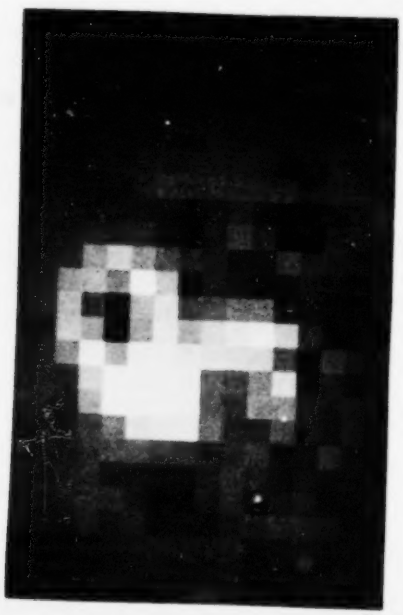
For the purpose of this study, the two smallest pixel sizes, 0.275 m^2 and 1.32 m^2, were easily rejected because of unwieldy amounts of data and signature widths. This elimination left a choice of either 3.65-m^2 or 14.59-m^2 pixels. Unfortunately, nothing between these choices was available. Woods were best classified at the Columbia Generating Station study area by using a pixel size of 14.59 m^2, but the resolution of all resources generally was much more satisfactory with the 3.65-m^2 pixel.

We decided that resolution of as many resources as possible was the better choice, even though signature problems would arise. Thus, the loss of some smaller resources was avoided at the expense of better classification of grosser features. Therefore, the 3.65-m^2 pixel was selected for most of this study. The optimum ground resolution cell lies somewhere between the 3.65-m^2 and 14.59-m^2 choices available for this study.

a. Cell size = $0.275m^2$

b. Cell size = $1.32m^2$

c. Cell size = $3.65m^2$



d. Cell size = $14.59m^2$

Figure 16. Resolving power of various ground cell sizes for a portion of the Columbia Generating Station study area showing grassland and woods surrounding a sandblow, June 1976.

SEASONAL VARIATION

The seasonal development and senescence of vegetation are powerful influences to spectral reflectance (Olsen and Good 1961, Kiefer 1970, Knipling 1970, Thomson 1972). As the growing season progresses many spectral signature shifts occur. At any time some resource signatures may be confounded and some may be discrete. At an earlier or later time the resources that were confounded may be easily separated, whereas the formerly disjoint signatures may overlap. Our results support these findings and suggest that if data files from different dates could be registered, a compilation of unique signatures could be extracted from otherwise imperfect data sets. No single date allowed perfect separation of resources.

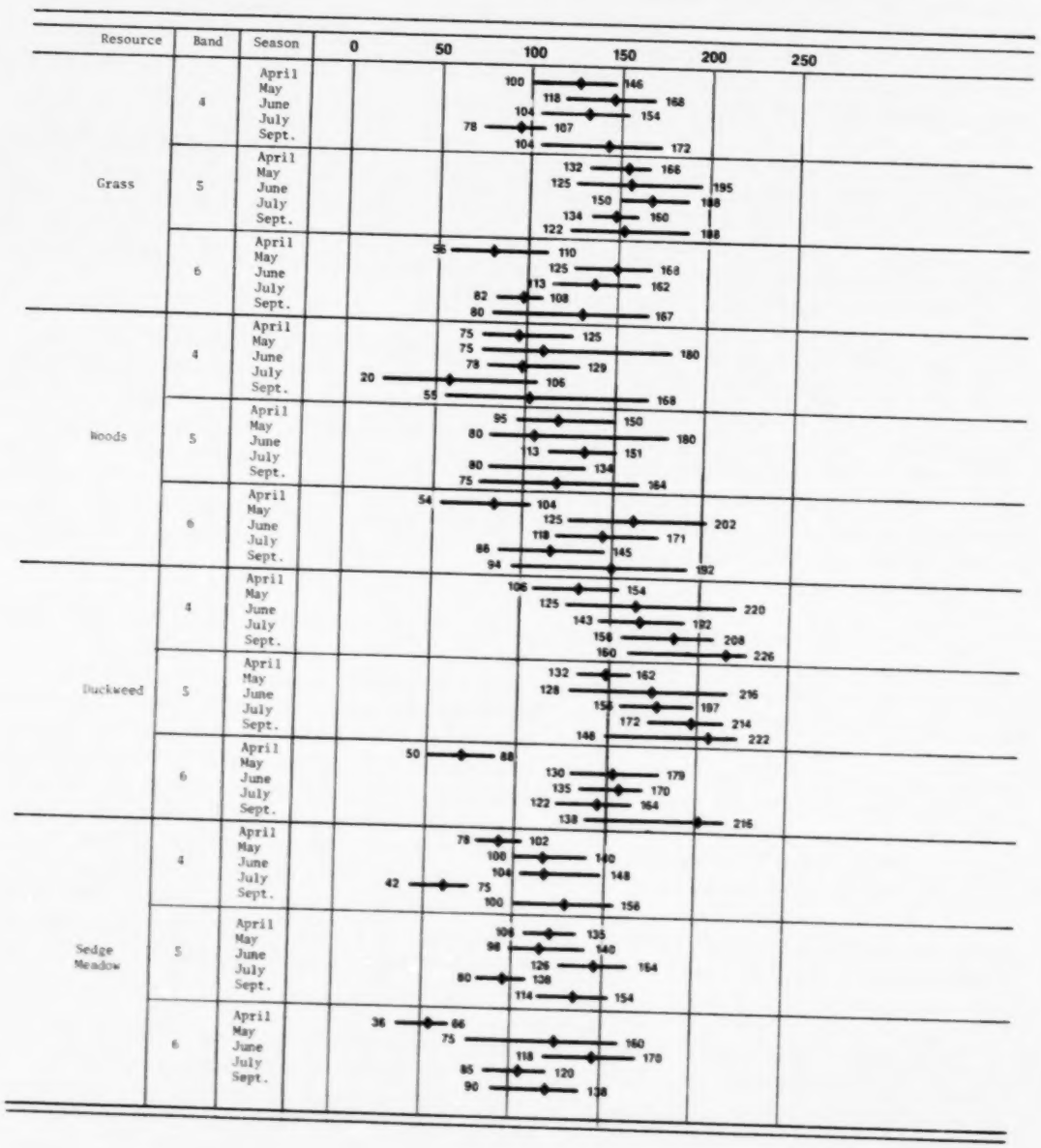
Seasonal change is obvious in images of the Columbia Generating Station study area from April, May, June, July, and September. Most striking is the extensive increase in infrared reflectance illustrated by the dominance of red dye in the July image. Another seasonal change relates to water levels. The spring imagery shows scattered open water areas that in later images either disappear or support floating macrophyte beds.

The effects of seasonal change are probably best illustrated by the change in individual resource signatures. Table 3 presents the signatures of woods, grassland, duckweed, and sedge meadow as digitized on images from the five dates. The quantitative relationships of seasonal signatures are unreliable, since the original exposure of the various images was not equal among the dates. The previously described algorithms for correcting and calibrating data attempt to reconstruct the original exposure values; among images taken on different dates, however, these original exposure conditions are bound to vary.

Despite the lack of quantitative reliability, several qualitative trends are evident. Infrared reflectance, as measured in band 6, increased considerably after April. Duckweed was the only resource that did not generally stabilize; it seemed to increase and grow brighter as the season progressed. Green reflectance, as quantified in band 4, was low in April and July. In April the vegetation was generally not green enough to predominate over the bare branches and dead vegetation remaining after winter. Green reflectance was low in July because in 1976 a drought was affecting plant growth. The drought persisted through September 1976, but the green reflectance in the September data was generally of greater magnitude than in the July data. Several things could account for this: (1) September data were not calibrated for lack of a film wedge; (2) July film may have been underexposed; or (3) some rain in September may have been sufficient to green the vegetation.

The most significant factor in these seasonal trends is the extent to which they facilitate the distinction of wetland from upland resources. This capability relates to national interests in wetland mapping and inventory (Anderson 1972). In April, woods and grassland could be successfully separated, as shown in the classifications of upland resources in Figure 11. Lowland resources, duckweed and sedge meadow, had distinct signatures. Woods could be discriminated from duckweed, and grass and sedge meadow were readily

TABLE 3. SIGNATURE BEHAVIOR OF GRASS, WOODS, DUCKWEED, AND SEDGE MEADOW FROM THE COLUMBIA GENERATING STATION STUDY AREA DURING THE GROWING SEASON APRIL 1977, MAY, JUNE, JULY, AND SEPTEMBER 1976



separated. Woods and sedge meadow had confounded signatures, however, as did grassland and duckweed.

The May signatures showed some improvement in the separability of the two upland resources from the wetland resources that were formerly highly confounded. Unfortunately, the distinction between grassland and sedge meadow was less complete in May than April. In June, the grassland signature was almost totally distinguishable from duckweed, but was somewhat confounded with sedge meadow. The woods were still incompletely distinct from sedge meadow, and duckweed was still disjoint from woods.

By July both wetland resources were entirely distinct from grassland. Of the four resources, the only problem was that woods and sedge meadow were almost entirely overlapped for all three bands. A possible solution to this problem would be to create a fourth file of textural data. The woods should have greater texture values than sedge meadow. If successful, this added textural information could make July data the best for classifying the four upland and lowland resources. Because woods and sedge meadow are major resources, their overlap would be a serious problem if textures are inseparable. Possibly the drought effects enhanced the separation of wetland and upland herbaceous communities more than would usually be the case for July.

September provided the poorest data in terms of differentiating resources. Only duckweed could be discriminated from the other resources; woods, grassland, and sedge meadow were all confounded. These difficulties could be due to the uncorrected condition of the data.

On the basis of these results, no optimum time seems to exist for digital analysis of vegetation. Various resources are best separated at various dates. This conclusion seems to contradict findings of Olson (1964), Lukens (1968), and Seher and Tuellar (1973), which indicate that late summer and early fall imagery are best for detailed vegetation mapping. Carter and Stewart (1975) suggest that multiseason imagery is the best approach for wetland classification. Aforementioned differences between computer discrimination of digital information and human qualitative judgments explain the situation. The more simple computer classifiers used in this study do not rely heavily on the importance of patterns and spatial association, whereas manual interpretations take advantage of these attributes. In contrast, digital information affords a more detailed division of tonal change than can be achieved manually. Therefore, comparisons of optimum time between digital analysis and manual analysis may be unreasonable.

Reliance on one year's data is inconclusive, especially with all the inherent uncontrolled variables such as climate, exposure, and registration of training sets. If the most distinct data bands from available dates could be registered and combined in one data file, however, a relatively powerful classification could ensue (Steiner 1972, Hauska and Swain 1975, Svedlow et al. 1975).

GENERALITY ATTRIBUTES

The study of generality attributes involved the study of signature stability and extendability. As mentioned previously, the time and expense of large-scale classification are closely related to the generality of resource signatures. The discussion on efficiency following this section will detail the costs of various steps in the classification process, but we note here that selecting training sets and identifying resource signatures are among the most time-consuming and critical steps. If a resource signature, derived from a training set in one scene, can be generalized for all occurrences of that resource in the one scene, further selection of training sets of that resource is unnecessary. Of greater import is determining whether the resource signature will hold for occurrences of that resource in other images given some reasonable controls. Use of controls would require that the images be taken on the same roll of film within a short time span under similar lighting conditions.

Imagery dated 3 October 1975 was available for two scenes: Hook Lake and Waubesa Marsh (Figure 1). These scenes portray a mixture of lowland and upland resources with several resources in common. Because they were photographed on the same day with one roll of film in a short time span, an ideal situation was created for testing the extendability of resource signatures. The signatures of representative resources from each scene are shown in Table 4.

Although some differences could be expected because of such factors as varying moisture regimes and vegetation density, the signatures for each of the five resources were surprisingly alike. Especially similar were the signatures for the two agricultural resources, corn and alfalfa, probably because they are monotypic, controlled resources with smooth textures.

The variation between the signatures for woods at Hook Lake and Waubesa could be caused by the amount of shadow included in the training sets. Purely shaded spots were classified separately from woods; however, some intermediately shaded pixels were included while delineating the training sets for woods, and the control over this delineation was arbitrary. As previously mentioned, the crown tops in the woods were irregularly colored. Thus, the woods signatures differed by as much as 10% in one band. Another source of variation was that the woods signatures, as presented, are a compilation of several training sets for each scene. A conscientious effort was made to capture the full spectral range of each resource signature, but the presence of unclassified pixels indicates that the signatures were never discerned with perfect accuracy.

The signature of constructions (built-up) for Hook Lake is based on very few pixels because very few constructed resources occurred in the scene. Since these constructions were largely narrow roads and small residences, selecting training sets was difficult. Edge effects may account for the slightly lower signature values of the Hook Lake constructions.

Sedge meadow was a highly variable resource depending on moisture conditions and species composition. At Waubesa Marsh the sedge meadows were

Table 4. SIGNATURES OF CORN, WOODS, CONSTRUCTIONS, ALFALFA, AND SEDGE MEADOW IN THE HOOK LAKE AND WAUBESA MARSH STUDY AREAS
OCTOBER 1976

Resource	Band	Scene	0 50 100 150 200 250
Corn	4	Hook Lake	136 — 197
		Waubesa	135 — 183
	5	Hook Lake	179 — 217
		Waubesa	171 — 210
	6	Hook Lake	113 — 143
		Waubesa	111 — 144
Woods	4	Hook Lake	58 — 142
		Waubesa	52 — 152
	5	Hook Lake	108 — 176
		Waubesa	94 — 181
	6	Hook Lake	84 — 162
		Waubesa	91 — 169
Constructions	4	Hook Lake	184 — 255
		Waubesa	189 — 255
	5	Hook Lake	184 — 233
		Waubesa	190 — 255
	6	Hook Lake	92 — 158
		Waubesa	107 — 187
Alfalfa	4	Hook Lake	84 — 135
		Waubesa	81 — 139
	5	Hook Lake	112 — 165
		Waubesa	111 — 169
	6	Hook Lake	85 — 131
		Waubesa	95 — 129
Sedge Meadow	4	Hook Lake	78 — 108
		Waubesa	63 — 102
	5	Hook Lake	113 — 130
		Waubesa	95 — 129
	6	Hook Lake	85 — 106
		Waubesa	76 — 111

codominated by tussock sedge (Carex stricta), bluejoint grass (Calamagrostis canadensis), and several species of forbs. The tussock sedge and forbs have a lower reflectance than bluejoint. At Hook Lake forbs were absent in the sedge meadows. Therefore, although the signature at Hook Lake was largely within the spectral range recorded for Waubesa sedge meadows, it was concentrated at the higher end.

Overall, this aspect of the study indicated that resource signatures might be generalized among images when: (1) the images are from the same roll of film, (2) the images are taken on the same day, (3) the images are digitized at the same time with uniform calibrations, (4) training sets are for nearly identical resources in terms of composition and physiognomy, and (5) scale is standard. This ability to generalize could be tested by classifying one scene with the training-set statistics of a different scene. Although the present study did not go beyond comparing signatures, further study along these lines may be worthwhile.

The situation often arises in which one or more of the five aforementioned conditions are not met and yet the generalization of resource signatures is desired. To test this situation corn and alfalfa data from Hook Lake and Waubesa Marsh, which had very stable signatures, were compared with corn and alfalfa data from Waunakee Marsh (Table 5). The conditions for generalizing resource signatures were met except that the data were digitized with different machine calibrations and were corrected with a slightly different algorithm.

To test if all resource signatures can be standardized on the basis of the relationship of signatures for one or two resources, the signature relationships of corn and alfalfa were calculated for each band. This calculation was done by using a simple ratio of the means; for bands 4, 5, and 6 the ratios between the Waunakee signatures and Waubesa-Hook Lake signatures were 0.75, 0.73, and 0.83, respectively, for corn, and 0.73, 0.74, and 0.83, respectively, for alfalfa. The similarity of these simple ratios suggests that standardization should be valid for these resources. In fact, when corn and alfalfa signatures were corrected by using the corn-signature relationships for each band, the results were as good as if the data were scanned and calibrated in the same way (Table 5). The variable condition was successfully standardized.

This approach was not as successful with naturally occurring vegetation communities, probably because the signatures of native plant communities are not as stable as cultivated crops. Because of this possible discrepancy, the signature for woods at Waunakee Marsh was adjusted using the relationship of corn signatures between Waunakee Marsh and Hook Lake-Waubesa Marsh. The results are shown in the last entries of Table 5. The unadjusted signatures for woods at Waunakee Marsh are actually closer to those for Waubesa-Hook Lake than the "corrected" ones in bands 4 and 5.

The problem with this attempt to generalize resource signatures rests most likely on the difficulty of accurately portraying natural vegetation signatures. The concept of standardization is probably valid for perfectly valid resource signatures. Smooth cultured resources such as crops and

TABLE 5. MEAN SIGNATURES FROM HOOK LAKE-WAUBESA MARSH STUDY AREAS AND FROM WAUNAKEE MARSH STUDY AREA BEFORE AND AFTER STANDARDIZATION BY USING A SIMPLE RATIO OF MEAN CORN SIGNATURES, OCTOBER 1976

Resource	Band	Scene	0 50 100 150 200 250
Corn	4	Waubesa-Hook L.	136 197
		Waunakee	106 141
		Waunakee (corrected)	141 188
	5	Waubesa-Hook L.	171 217
		Waunakee	140 166
		Waunakee (corrected	179 212
	6	Waubesa-Hook L.	111 144
		Waunakee	90 122
		Waunakee (corrected)	108 146
Alfalfa	4	Waubesa-Hook L.	81 139
		Waunakee	58 102
		Waunakee (corrected)	77 136
	5	Waubesa-Hook L.	111 169
		Waunakee	75 131
		Waunakee (corrected)	96 168
	6	Waubesa-Hook L.	85 131
		Waunakee	62 119
		Waunakee (corrected)	75 143
Woods	4	Waubesa-Hook L.	52 152
		Waunakee	46 147
		Waunakee (corrected)	61 196
	5	Waubesa-Hook L.	94 181
		Waunakee	84 159
		Waunakee (corrected)	107 203
	6	Waubesa-Hook L.	84 169
		Waunakee	62 140
		Waunakee (corrected)	75 168

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constructions lend themselves to signature identification, and therefore to standardization, but natural vegetation resources do not. Therefore, the overall success of such standardization efforts may be limited.

COST-TIME EFFICIENCY

Perhaps the first question asked by anyone wishing to use digital film analysis is what it costs. Even if the capabilities of digital analysis are suited to a particular inventory or mapping problem, the cost of producing a finished product must be compared to alternative techniques such as manual photointerpretation or ground surveys (Aldred 1972, Grinnell and Conway 1972). The following discussion attempts to present the costs of digital analysis on the EMDAG system. It is important to remember that these costs are for digitally and manually interpreting a single 70-mm image comprising about 1 square mile and 100,000-pixel data base.

All computer work in this study was performed on a UNIVAC 1110 computer operated by the Madison Academic Computing Center (MACC) of the University of Wisconsin. The computer costs reflect the rates charged by MACC for their services. These costs may vary for other users depending on the rates charged by their computer service or on the existence of in-house computing services. The efficiency of computer-user interaction also greatly affects the time and cost. The speed of assembling and executing computer jobs may vary greatly for someone keypunching runstream card decks and someone directly wired to the computer through an interactive color terminal. As described by Ballard and Eastwood (1977), this method of cost accounting is accurate for the "home system" but is somewhat inflexible.

Nearly all the computer runs for this project were assembled and executed on a 30-character-per-second hard-copy interactive terminal. Most output was from an MACC line printer. The time and expenses for producing a basic supervised digital classification are shown in Table 6. The time entries represent the time required for manual operations of compiling and entering runstreams and data. Cost entries are in three columns: The first represents the cost of executing the specific program; the second includes the associated charges for paper, tape utility, and file utility; and the third equals the cost of one run multiplied by the typical number of iterations necessary to achieve a successful classification. Other types of classifications and data enhancements entail some additional costs (Table 7).

The information in Table 6 can be further grouped into general stages of processing. First, the initial raw-data generation involved digitizing, checking the file, correcting the data, and selecting a representative subset. The initial creation of a usable digital data set required about 1.5 h and cost nearly $50. This process was the most cost intensive.

Surprisingly, the manual interpretation and ground survey efforts were not the most time-consuming steps. This stage of the process required about 5 h, which included the time for tracing and tentatively identifying all resources shown in Figure 12 and ground checking. The travel costs of this aspect of the study were negligible because the locales were nearby. If a distant area were being surveyed, the expense of visiting the area could be

TABLE 6. TIME AND EXPENSES OF A BASIC FILM ANALYSIS WHEN UNIVERSITY OF WISCONSIN EMDAG SOFTWARE PACKAGE AND MACC COMPUTING SERVICES ARE USED

Operation	Time (min.) Each run	Time (min.) Total	Cost ($) Program incl. pages etc.	Iterations	Total cost
Scanning 70 mm image on densitometer at 100 aperture (tape)	20	20	$12.00	1	$12.00
File check with PRINT program	10	20	1.25	2	2.50
Create characteristic curve D vs. logE	5	5	2.00	1	2.00
Create raw data file with OPTRON ptrgram 100 tracks = 150,000 pixels	5	5	3.00	1	3.00
Calibrate data with CORRECT program	5	5	1.50	1	1.50
View data set with SLICE	5	10	4.00	2	8.00
Reduce data with SUBSET	10	20	1.20	2	2.40
Overprint presentation with SLICE	5	10	3.00	6	18.00
Ground truth					
Manual interpretation	120	120		1	
Ground survey	180	180		1	
Select training sets (80 sets)	75	120		3	
(Additions)	(20)				
Record training sets	135	180		3	
(Additions)	(20)				

(continued)

TABLE 6 (continued)

Operation	Time (min.) Each run	Time (min.) Total	Cost ($) Program incl. pages etc.	Iterations	Total cost
Run training set program TRAIN (Additions)	20 (10)	40	$1.00 (0.25)	3	$1.50
Look at signature histograms with HSGRAM (Additions)	3 (3)	9	6.00 (1.50)	3	9.00
Look at signature bar diagrams with CLASSBAR	3	9	1.00	3	3.00
Modify training sets with MODSET	30	90	0.75	3	2.25
Box classification with BOX4 (Additions)	60 (20)	100	5.00	3	15.00
For reducing noise SMOOTH neighborhoods of nine pixels, two iterations	10	20	3.50	2	7.00
Classes assigned colors with COLOR	20	40	1.00	2	2.00
File prepared for film writing with FILM70	10	20	2.75	2	5.50
Writing and developing film	60	120		2	
Total	13h 11min	19h 3min	$48.95		$94.65

TABLE 7. ADDITIONAL TIME AND EXPENSES FOR DATA ENHANCEMENTS, TRANSFORMATIONS, AND MORE SOPHISTICATED CLASSIFICATIONS IN DIGITIZED FILM ANALYSIS WHEN THE UNIVERSITY OF WISCONSIN EMDAG SOFTWARE PACKAGE AND MACC COMPUTING SERVICES ARE USED

	Time (min.)		Cost ($)		
Operation	Each run	Total	Program incl. pages etc.	Iterations	Total cost
Enhance data with FILM RATIO	5	5	$1.75	1	$1.75
Enhance data with TEXTURE	5	5	3.00	1	3.00
Enhance data with canonical TRANSFORM	10	10	2.00	1	2.00
Calculate training set statistics with STATS	5	10	0.25	2	0.50
View elliptical signature dimensions with ROTRAIN	3	3	0.25	1	0.25
Load elliptical signatures into look-up table with LOADE3 or LOADE4 (30 class)	20	40	3.00	2	6.00
Elliptical classifier TABCLASS (w/o minimum distance applied)	10	20	5.00	2	10.00
TABCLASS (w/minimum distance applied)	10	20	15.00	2	30.00
Total	1h 3min	1h 53min	$26.10		$53.50

more than the entire digital analysis. Another tempering thought is that the manual efforts were directed at identifying representative resources in the hopes that the signatures of all resources could be represented. Once a resource was located on the ground and registered on the digital data base, little further effort was expended toward locating all other occurrences of that resource. A totally manual effort would require a more conscientious effort to accurately locate, register, and map every resource and all occurrences.

The next general category of processing was the location of training sets and the determination of signatures. This step was by far the lengthiest, taking over 9 h, nearly half the total analysis time. This step more than any other could be expedited by use of an interactive color terminal to eliminate the necessity of scrutinizing line-printer output.

The classification segment of the process takes only one-tenth the total time, but represents roughly one-fourth the total expense. With luck, three iterations of a classification as shown in the cost estimate are not needed. However, a first classification does not usually characterize all resource occurrences completely. The remaining time and money are allocated for preparing a film image of the classification. Three hours and $7.50 were typically consumed in this endeavor. The costs of film and chemicals were not included.

With more elaborate and sophisticated methods of data enhancement (such as ratios, canonical transformations, and texture quantification) or classification (elliptical classifier and minimum distance classifier), the expenses of achieving a satisfactory classification may be inflated an extra $20 to $50. Little additional time is expended for these processes.

Economies of scale heavily influence the total process cost. An economy of scale can be realized by decreasing the scale of the imagery; the data set is quartered by halving the scale. Although the efficiency of locating training sets is enhanced, file maintenance is cheaper, and the paper costs are reduced, nevertheless, the savings are not very substantial because every step of the process must still be performed.

Substantial savings can be realized by the ability to classify an entire roll of film based on the signatures of representative resources taken from the first image or two on the roll. Subsequent image classifications may require signature augmentation; however, the major time factor in digital analysis is the processing of training sets. Any reduction in this aspect of the analysis should result in significant savings. Therefore, aerial photographic missions should be carefully planned so that all desired scenes are included with exposure and processing variables reduced as much as possible.

In comparing digital film analysis to ground survey and manual interpretation, the scale is a very important consideration. For single images where quantification of resources is not important, digital analysis is not competitive with a manual approach. Digital analysis may become more efficient where very complex resource patterns exist, such as roadways and

houses mixed with vegetation in an urban area. When quantification of the areal extent of resources is desired, a manual interpreter must use a planimeter, grid overlay, or weighing technique to achieve what a digital analysis inherently accomplishes.

An important consideration for potential users of this technology is that classification success is not assured. The documented costs of processing digitized film information may be applied to a wholly unsatisfactory classification effort. Careful scrutiny of resource signatures after selection of training sets should decide the issue of whether to proceed with the highly cost-intensive classification portion of the process.

ACCURACY

The primary goal of a digital film analysis is to separate and classify selected resources. In most cases the success depends on the level of detail desired and the complexity of the resource base.

Other researchers in digital image analysis have had various rates of success. Unfortunately, the methods employed to quantify the accuracy were seldom, if ever, documented. Doverspike et al. (1965) suggested that color densities alone would not be sufficient to classify land use successfully; by comparing signatures manually the success rate averaged only about 65%. Studies limited to gross-resolution satellite data (Bauer and Cipra 1973, Goodenough and Shlien 1974, Owen-Jones 1977) approached success rates of greater than 90% for classification schemes incorporating simplified resource categories. Owen-Jones (1977) recognized that detailed digitized film analysis of vegetation complexes presented problems of signature complexity that reduced accuracy. Detailed studies of forest species with several bands of multispectral imagery by Rohde and Olsen (1972) achieved accuracies of nearly 85% correct identification, but they acknowledged that tree signatures overlapped badly with those of adjacent fields. Wacker and Landgrebe (1972) achieved success rates of about 60% in separating a few crop types by using scanned film and several classifiers.

The scenes analyzed in this study presented fairly complex associations of vegetation, water, and structures. The highest possible level of detail was sought. Most vegetation types were separated on the basis of classical ecological concepts of association.

The various classification attempts met with mixed success. Even with properly selected training sets, confounded resource signatures were common. If these represented major resources, the scene would probably be poorly classified. Some of the problems were due to physiognomic similarities among associations. For example, wetland areas with a canopy dominated by forbs such as aster (Aster sp.), goldenrod (Solidago sp.), and joe-pye-weed (Eupatorium sp.), and a very dense tussock sedge ground layer would properly be classified as sedge meadow. Upland old fields and other vegetation types with a forb canopy were commonly confounded with the sedge meadows described above. Although the goal was to separate these vegetation types, the signatures did not permit separation. Possibly, a finer resolution might allow identification of separate signatures for the forb species, and the

associations could be split into their component species. However, as discussed in the previous section on resolution, this amount of detail is counterproductive. Resources must be defined such that groups of pixels can be delineated for training sets. Resolution not only relates to the size of a single pixel, but also to the required occurrence together of a minimum of four pixels of a like resource to form a training set. As the resolution becomes progressively finer, the erratic signatures increase and the uniformity of association signatures decreases.

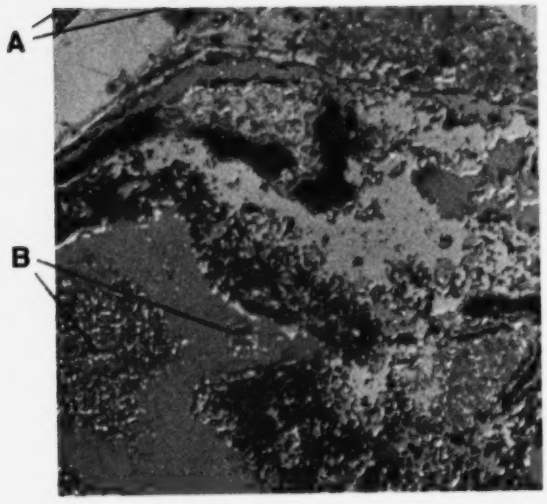
On the other hand, if resolution is allowed to become less fine, greater classification success can be achieved but only for gross classes of vegetation and other resources. For example, a study of impervious surfaces would attempt to separate all vegetation as one class distinct from impervious surfaces or bare soil. This low level of detail would not be satisfactory for most inventories of general land resources. However, as shown in Figure 11, screening lowland from upland resources simplified the classification effort and provided success in this study.

The above discussion is not meant to imply that detailed classifications of plant associations are impossible. We found that when the associations are phenologically distinct they can be successfully separated. Typically this meant that the associations were either heavily dominated by a single species (such as cropland) or that the association codominants were distributed in such a way that a homogeneous signature was reflected.

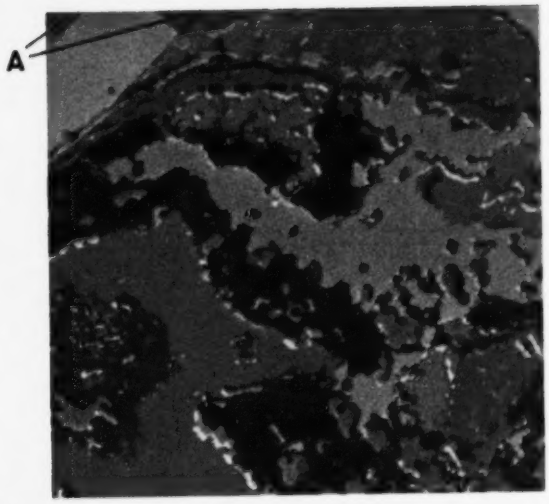
The latter situation occurred at Hook Lake, an acid bog. The classic bog community is characterized by distinct zonation of vegetation types. This is illustrated in Figure 1b where a central stand of tamarack is encircled by leatherleaf over a sphagnum mat, which is in turn surrounded by an uneven zone of wiregrass sedge. The bog is bordered by a moat of open water. Cattail are proximate to the edges of open water, and some mixed macrophyte beds of pickerel weed, arrowhead, and duckweed occur in the water. The uplands had assorted cropland and mixed oak hardwoods woodlots, some of which were confounded with the lowland resources.

The classifications of the Hook Lake scene shown in Figure 17 were the most successful classifications of a vegetation complex attempted and are considered representative of the maximum classification accuracy for complex vegetation types when the described classifiers are used. Accuracy was measured by direct comparisons between the classifications and a blowup of the scanned image written back onto film in its scanned form (Figure 13). Random pixels from the classifications were compared to their counterparts on the original scanned image, and a decision was made on the correctness of the classified pixel. This decision was based on the manual interpretation map and in reference to the original photo.

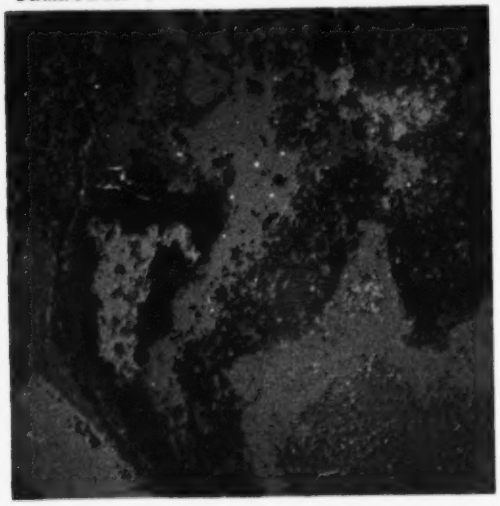
An index of accuracy was then derived by calculating the percentage of correctly identified pixels. This general index was presented in the form of a confusion matrix which showed the classification success of individual resources and those that were confounded. The results of this tally for the unsmoothed, fully supervised parallelepiped classification are shown in Table 8. Of the 200 randomly sampled pixels, 147, or nearly 75%, were correctly



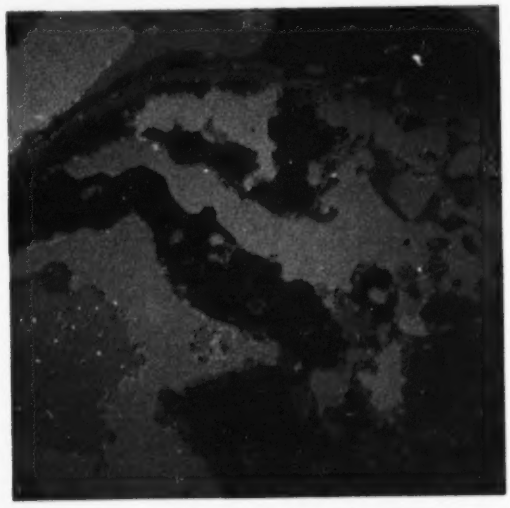
a. Unsmoothed parallelepiped; green= cattail, olive=wiregrass, lt. orange=leatherleaf, dk. orange= woods, beige=emergents*, blue= water, dk. green=deep water, yellow=corn, red=alfalfa[A], maroon= tamarack[B].



b. Smoothed parallelepiped; green= cattail, brown=wiregrass, dk. orange=emergents*, blue=water, dk. brown=deep water, yellow=corn, red= alfalfa[A], maroon=tamarack.



c. Unsmoothed elliptical; lt. green= cattail, dk. green=wiregrass, orange=leatherleaf, dk. gray=woods, pink=emergents*, blue=water, dk. blue=deep water, lt. red=alfalfa, yellow=corn, teal=tamarack.



d. Smoothed elliptical: Same color key as unsmoothed elliptical.

Figure 17. Classifications of the Hook Lake study area, October 1976.

*Emergents were predominantly arrowhead.

TABLE 8. CONFUSION MATRIX FOR THE UNSMOOTHED PARALLELEPIPED CLASSIFICATION OF THE HOOK LAKE STUDY AREA.[a]

	Computer Class												
Ground Identity	Cattail	Leatherleaf	Water	Emergents	Tamarack	Wiregrass	Upland Woods	Alfalfa	Corn	Edge	Shade	Unidentified	Accuracy percentage minus omissions
Cattail	20				1								95
Leatherleaf		32		1			3			1	1		84
Water			34								4		90
Emergents				4								1	80
Tamarack					5	1	1						71
Wiregrass					5	25	1						81
Upland Woods		2		4			10			1		1	56
Alfalfa	1	1		4				3		1		2	25
Corn									11				100
Edge				3			3			3		1	30
Shade			9										0
Accuracy percentage minus commissions	95	91	79	25	45	96	56	100	100	50	0		

[a] The number and percentage of pixels of each resource properly and improperly classified are shown (overall accuracy of 74.5%).

classified. One-fourth of the improperly classified pixels resulted from the confusion of water and shade, both essentially black. If this single pair of confounded entities were united, the accuracy would be improved to more than 80%.

In view of the importance of separating wetland resources from upland resources, it is interesting that of the incorrect pixels 66% represented wetland resources confounded with upland resources, nearly 20% were confounded upland resources, and only 15% were among wetland resources. This suggests both that higher classification success can be achieved for scenes including exclusively upland or exclusively lowland resources and that when photographed together the separation of these resource types is difficult.

Resources having the highest classification success included cattail, leatherleaf, wiregrass sedge, water, and corn. The most poorly classified resources included shade, alfalfa, edge, trees, and tamarack. The difficulties encountered with the latter resources were not surprising because of aforementioned textural or seasonal limitations. If these limitations could be overcome, and these "problem" resources better classified, the accuracy would be improved to greater than 90%.

The accuracy for an elliptical classifier employing a minimum distance routine for overlapping signatures is presented in Table 9. The overall classification success was 72%. Among the more easily classified resources were leatherleaf, water, alfalfa, and corn. Over one-fourth of the misclassified pixels were transitional or edge pixels. Nearly 80% (44 of 56) of the misclassified pixels involved trees. Although the elliptical classifier more accurately portrayed texturally smooth resources, it did not make use of textural information and was thus hindered in separating roughly textured resources.

One approach to eliminating aberrant pixels from a classification is to apply a smoothing routine to the classification whereby each pixel is compared to its neighbors, much like the texture routines. If the neighborhood of a pixel is uniformly different from the pixel itself, the pixel is defined as erratic and is reclassified to match its surrounding neighbors. For extremely complex scenes where resources may be accurately portrayed by small groups or even single pixels, the smoothing routines probably detract from the accuracy. For relatively expansive resources, however, such as crops, woodlands, or meadows, a smoothed version may be more accurate. This hypothesis was tested by examining the same 200 pixels used in the previous accuracy tests and comparing them to a smoothed version of the same classifications (Figure 17). Table 10 and Table 11 present the results of these comparisons.

The overall accuracy of the parallelepiped classifier was improved to 84.5% for the smoothed version (Table 10). Tree classes (tamarack, shade, and upland woods) accounted for nearly 70% of the problems; the accuracy of the smoothed classification, discounting problems due to trees, would have been 93.7%.

Equally good classification accuracy (84.5%, Table 11) was achieved by the smoothed elliptical classifier (Figure 17). All classes were consistently

TABLE 9. CONFUSION MATRIX FOR THE SMOOTHED PARALLELEPIPED CLASSIFICATION OF THE HOOK LAKE STUDY AREA.[a]

	Computer Class												
Ground Identity	Cattail	Leatherleaf	Water	Emergents	Tamarack	Wiregrass	Upland Woods	Alfalfa	Corn	Edge	Shade	Unidentified	Accuracy percentage minus omissions
Cattail	22												100
Leatherleaf		39											100
Water			35								1		97
Emergents		1		6								1	75
Tamarack			1		7	1							78
Wiregrass					1	28							97
Upland Woods		3		2			13			1		1	65
Alfalfa		2		7				3		1		1	21
Corn									12				100
Edge				1			3			3			43
Shade			3								1		25
Accuracy percentage minus commissions	100	87	90	38	88	97	81	100	100	60	50		

[a] The number and percentage of pixels of each resource properly and improperly classified are shown (overall accuracy of 84.5%).

TABLE 10. CONFUSION MATRIX FOR THE UNSMOOTHED ELLIPTICAL TABLE LOOK-UP CLASSIFICATION OF THE HOOK LAKE STUDY AREA.[a]

	Computer Class												
Ground Identity	Cattail	Leatherleaf	Water	Emergents	Tamarack	Wiregrass	Upland Woods	Alfalfa	Corn	Edge	Shade	Unidentified	Accuracy percentage minus omissions
Cattail	20				3	3	1						74
Leatherleaf		24					4						86
Water			24								3		89
Emergents				6			2				1		67
Tamarack					12	1	2					1	75
Wiregrass					4	21	3					1	72
Upland Woods		2		6			10	1				1	50
Alfalfa				3				13					81
Corn									11				100
Edge		1		1	3		8	2					0
Shade											2		100
Accuracy percentage minus commissions	100	89	100	38	55	84	35	81	100	0	33		

[a] The number and percentage of pixels of each resource properly and improperly classified are shown (overall accuracy of 71.5%).

TABLE 11. CONFUSION MATRIX FOR THE SMOOTHED ELLIPTICAL TABLE LOOK-UP CLASSIFICATION OF THE HOOK LAKE STUDY AREA.[a]

	Computer Class												
Ground Identity	Cattail	Leatherleaf	Water	Emergents	Tamarack	Wiregrass	Upland Woods	Alfalfa	Corn	Edge	Shade	Unidentified	Accuracy percentage minus omissions
Cattail	23				3							1	85
Leatherleaf		30										1	97
Water		1	21			2					3		78
Emergents				9									100
Tamarack		1			13	1							87
Wiregrass					1	27	1						93
Upland Woods							21					2	91
Alfalfa				1			1	14					88
Corn									11				100
Edge		1			3		6	1					0
Shade		1											0
Accuracy percentage minus commissions	100	88	100	90	65	90	72	93	100	0	0		

[a] The number and percentage of pixels of each resource properly and improperly classified are shown (overall accuracy of 84.5%).

better identified than in the unsmoothed version except for water, shade, and transitional. Because the resolving power of the smoothed classification is essentially degraded, the more intricately expressed resources, such as the three listed, are expected to classify less successfully.

Although the same overall classification accuracy was attained for the smoothed box classifier and smoothed elliptical classifier, their relative success with individual resources varied. Wooded resources (tamarack and upland woods), alfalfa, and mixed emergents were much better classified with the elliptical classifier. Water and cattail were more successfully identified with the box classifier.

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